Human Capital Analytics

An Investigation of Success Factors, Methods, and Basic Assumptions

Thesis

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To my family.

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Introduction

The intention of human resource (HR) practitioners to demonstrate the value of what they do for the rest of the organization has a long tradition (Wright, Gardner, Moynihan, & Allen, 2005). Currently, HR is at a critical point, as it stands between becoming a true strategic business partner and disappearing into oblivion, as there is much debate about its relevance and contribution to the bottom-line today (Chew, Girardi, & Entrekin, 2005; Jamrog & Overholt, 2004; Lawler & Mohrman, 2003). The desire to demonstrate this contribution has driven recent developments in the field of human capital analytics, a term referring to processes „for using quantitative methods to transform data relating to individuals and groups of people (such as their attributes, skills, development, costs, productivity) into actionable business intelligence that can help to drive and improve an organization's most important outcomes" (Bassi & McMurrer, 2009, p. 1).

The human capital analytics topic stems mainly from two scientific domains. On the one hand, it is associated with the field of economics with the goal of "putting human capital on the balance sheet" (Boudreau & Ramstad, 2003, p. 200). On the other hand, it falls into the domain of I/O psychology, having a long research tradition when it comes to quantifying HR investments and their impact on business results (Boudreau & Ramstad, 2003; Cronbach & Gleser, 1965; Wright et al., 2005). This thesis deals with the I/O psychological perspective of human capital analytics and joins its research tradition.

In the following, I will first introduce a broad perspective of what human capital analytics is concerned with. Then I will describe three aspects of this topic in greater detail, namely the success factors of such information, the most important methods that can be applied, and some of the basic underlying assumptions and challenges, and argue why these topics are of particular

importance for the development of this field. Subsequently, I will present the aim of this thesis and state its main research questions. Finally, I will briefly summarize the contents of the three studies outlined in this thesis.

Human Capital Analytics and Human Capital Information

As mentioned before, human capital analytics can be seen both from an economics perspective, and from an I/O psychological perspective. The economic perspective includes topics such as financial efficiency measures of HR operations (e.g., Bontis & Fitz-enz, 2002; Cascio, 2000; Fitz-enz, 2000), HR costing and accounting (e.g., Flamholz, 1999), and the measurement of corporate investments in human capital (e.g., Bassi, Lev, Low, McMurrer, & Seisfeld, 2000). It relies on standard financial statements and accounting logic that may be compelling to external financial analysts and internal controllers of an organization.

The I/O psychological perspective, with which this thesis is concerned, can be described as a human capital analytics approach that is based on putting together disparate pieces of employee-related information in a way that makes it possible to identify previously unknown relationships between various data elements. Most often, information on the "people side" of an organization (e.g., its work, learning, and leadership environment) is usually captured through an employee survey (B. Schneider, Ashworth, Higgs, & Carr, 1996). Employees in different locations or with different managers will be working in somewhat different environments, and their survey responses will vary accordingly. This information can be combined with other data elements, such as information on an organization's sales office productivity or customer satisfaction that may exist in a different database, often housed and managed elsewhere in the organization (Bassi & McMurrer, 2009).

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The terms “human capital analytics” and “human capital information” are closely related. While human capital analytics refers to the process side, HR information refers to the data elements involved in this process. HR information can be defined as all information concerning an organization’s human resources such as head count, fluctuation, composition of talent pools, use and effectiveness of training and development initiatives, results from employee surveys, performance management, utility analysis, succession planning, age distributions and other forms of workforce-related information (Lawler, 2008).

Success Factors

To date, much research has considered which metrics are the most relevant: Researchers from disciplines as diverse as accounting (e.g., Echols, 2005), finance (e.g., Bryan, 2007), and operations management (e.g., C. Schneider, 2006) compete to define the latest indicators for human resources within organizations (Boudreau & Ramstad, 2007). The “metrics challenge” (Huselid, Becker, & Beatty, 2005, p. 63) is addressed in a variety of books, proposing a universe of HR indicators and strategies to face managers’ need for valuable HR information (Boudreau & Ramstad, 2007; Cascio & Boudreau, 2008).

However, much less research has considered what criteria such information needs to fulfill, in order to be valuable for its target audience. Without having a clear understanding of the variables that determine the value of HR information, the tremendous effort undertaken by practitioners and academics is running the risk of missing its main target, which is the improvement of HR decisions. This question appears to be even more important in light of the fact that it has been left unanswered in past decades, resulting in decreased interest in available solutions such as utility analysis (Boudreau & Ramstad, 2003; Choragwicka & Janta, 2008). Even though some attempts have been made in the past decades to tackle the question of which

criteria such information needs to hold (e.g., Haines & Petit, 1997; Voermans & Van Veldhoven, 2007), a sound theoretical framework to explain managerial acceptance of such information so far is largely missing.

Methods of Human Capital Analytics

The economic methods mentioned previously rely on standard financial statements and accounting logic that may be compelling to financial analysts and controllers, but also acknowledge the limitations of financial analysis to account for human capital or intangible assets (Lev, 2001). More importantly, they may be limited in their ability to inform decisions about HR program investments (Boudreau & Ramstad, 2003). This thesis focuses on human capital analytics procedures that are concerned with the methods of generating valuable information required by internal stakeholders of an organization, such as HR- or front-line managers when it comes to making decisions about investments in HR initiatives. This information is intended to improve people-related decisions (Cascio & Boudreau, 2008). Methods include single attribute utility analysis (e.g., Cronbach & Gleser, 1965), multi-attribute utility analysis (Roth, 1994; Roth & Bobko, 1997), HR dashboards (Huselid et al., 2005), balanced scorecards (Kaplan & Norton, 1992), or causal-chain analysis (e.g., Boudreau & Ramstad, 2003; Rucci, Kirn, & Quinn, 1998).

Again, the majority of research has been invested to develop and refine these methods. Research on the acceptance and usefulness of these approaches has been scarce, and evidence has been mainly anecdotal, rather than empirical (Lawler, Levenson, & Boudreau, 2004; Subramony, 2006) resulting in a decrease of interest in some of these methods (Cascio & Aguinis, 2008). One exception is the academic effort that was put into evaluating managerial acceptance of single attribute utility analysis.

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Single attribute utility analyses is based on the multiplicative combination of several components (e.g., the standard deviation of job performance expressed in monetary units, the validity of the HRM intervention, the number of participants) related to a specific selection, performance management, or training program. It transforms the utility of such a program into a single financial value. While research consistently provides evidence for mediocre levels of acceptance of single attribute utility analysis, little is known about the other methods of human capital analytics, such as those mentioned above.

Other methods, particularly those applied by consulting companies today (e.g., Bassi & McMurrer, 2007; Bassi & McMurrer, 2009) and for which anecdotal evidence is very much in favor of (Lawler et al., 2004; Subramony, 2006), focus on a different approach in which individual-level data from employee surveys are aggregated and mapped to higher-level measures of retention, performance, or customer satisfaction. This approach is called causal-chain analysis (e.g., Boudreau & Ramstad, 2003; Rucci et al., 1998). It provides the basis for decisions of whether to invest in human capital initiatives or not, based on statistical analysis of the linkage between employee attitudes or other factors measured in a survey, and outcomes relevant to informing HR policy (e.g., retention, diversity, and wellness). The insights from this linkage analysis are intended to provide HR professionals with actionable intelligence for guiding their strategies and optimizing their investments (Bassi & McMurrer, 2009).

Basic Assumptions Surrounding the Human Capital Analytics Topic

While this concept seems to be relatively simple, by combining information on the human side of the business with the business's bottom line to yield HR information that would not otherwise be possible, it does require close attention to detail (Bassi, 2009). Challenges arise out of three basic assumptions (Cascio & Boudreau, 2008).

First, the causal ordering of the included variables led to a long-lasting debate and extensive research about the question of which variables influence other variables in a causal sense. Nevertheless, research has been inconclusive regarding which causal direction might reflect the right assumption (Wright et al., 2005). For example, although many organizations invest large amounts of money into employee attitude surveys and use the results for developing actions pointed towards increased employee commitment, it is still just a hope that this finally leads to superior firm performance (e.g., B. Schneider, Hanges, Smith, & Salvaggio, 2003; Wright et al., 2005).

Second, the level of analysis should be considered, as it is important to understand how the connection between attitudes and organizational outcomes vary depending on the level of analysis (Cascio & Boudreau, 2008). For example it appears that, even when relationships at the individual level are weak (Riketta, 2008), there may still be strong relationships when the aggregated attitudes of employees are related to aggregated performance, e.g., at the business-unit level (Harter, Schmidt, & Hayes, 2002) or at the organizational level (B. Schneider et al., 2003) . Choosing the appropriate level of analysis is a matter both of the power of the statistical test and of the strategic question at hand. In most organizations, the fundamental strategic issues involve business-unit or work-group performance, so results suggesting that relationships may be more powerful at the business-unit level of analysis are encouraging (Cascio & Boudreau, 2008).

Third, the time lags for the adequate measurement are difficult to determine, as there is no consensus in the research literature about what the most appropriate time lag could be for the collection of the data (Cascio & Boudreau, 2008). The “right” measurement interval is important, for example, because sometimes, the organizational performance might even drop a bit after the implementation of a new management practice (Pil & MacDuffie, 1996) and a false specification of the timing interval might lead to biased, or worse, misleading results.

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Aim of the Thesis

The aim of the present thesis is to investigate three central questions surrounding the topic of human capital analytics. First, we were interested in success factors of human capital information. Second, based on insights from the first study, we compared two sources of HR information along these criteria. Third, we explored preconditions that are vital for some methods of HR information, including the method described in study 2. Therefore, we conducted three studies.

The aim of the *first study* was to identify the success factors HR information needs to hold in order to be valuable for organizational decision makers, with the term "valuable" referring to its ability to improve vital decisions about human resources (Cascio & Boudreau, 2008). The *second study* aimed to compare an established source of HR information (i.e., single attribute utility analysis) with a promising alternative (i.e., causal-chain analysis). The *third study* aimed to shed new light into basic assumptions surrounding the human capital analytics topic, including the potential causal ordering of job attitudes and business performance. The findings of these three studies should help to get more insight into the specify success factors of HR information, its methodologies, and basic assumptions. Finally, answers to these questions are intended to further drive theoretical development in the field of human capital analytics, and to improve the strategic impact of human resource practitioners.

Chapters' Overview

Below I present a short overview of the main foci of the chapters of this thesis. Each chapter covers one study. I refer to the study's theoretical background, the particular hypothesis tested, and the description of where the study expands previous research.

Chapter 1 presents a study that examined the success factors of HR information. We adapted the Technology Acceptance Model (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989) from the information systems field to the human resource context. Based on meta-analytic findings and theoretical considerations from the information systems field, we designed our model and hypothesized that the relations outlined in the Technology Acceptance Model are transferable to the HR information field. We tested our hypothesis with an online survey, yielding a sample of 179 bank managers. This is the first study that outlines the fundamental principles and variables that lead to successful HR information based on theoretical considerations from the information systems field.

Chapter 2 compares two methods of utility analysis. Utility analysis represents one form of HR information. In particular, we compared single attribute analysis (Brogden, 1949; Cronbach & Gleser, 1965) as the most established form of utility analysis (e.g., Choragwicka & Janta, 2008) with causal-chain analysis (Cascio & Boudreau, 2008). We embedded the topic into the theoretical framework of HR information success (Winkler, König, & Kleinmann, 2009) which outlines five constructs related to the success of HR information (i.e., understandability, information quality, perceived usefulness, information satisfaction, intention to use). We hypothesized that causal-chain analysis yields higher values on these five variables than single attribute utility analysis. Furthermore we hypothesized that the effect of a given utility analysis method on perceived usefulness and information satisfaction will be simultaneously mediated by understandability and information quality. To test our assumptions, we analyzed data from 144

human resource practitioners that were confronted with a decision scenario. This study is the first to provide empirical evidence for the appeal of causal-chain analysis to organizational decision makers and therewith extends the anecdotal evidence that has been provided so far (Lawler et al., 2004; Subramony, 2006).

The study in *Chapter 3* examined opposing assumptions about the potential causal ordering of employee job attitudes and business-unit performance. Furthermore it addresses the question of what might be the appropriate level of analysis and the "right" interval for measurement. Based on expectancy-based theories of motivation (e.g., Naylor, Pritchard, & Ilgen, 1980; Vroom, 1964), adaptation-level theory (Helson, 1964), and the endowment/contrast model (Cheng, 2004; Tversky & Griffin, 1991) we hypothesized that the influence of employee job attitudes on performance might be more persistent than vice versa. We tested our hypotheses over a four-year time span including four waves of data at the business-unit level of a Swiss bank. This is the first study in the field of linkage research that examines likely causal relations and timing issues within a four-wave data set at the business-unit level including both financial performance and customer satisfaction.

In the *general discussion* I will discuss the findings of the three studies out of an overall perspective, describe particular strengths and weaknesses of the research presented, and end with implications for future research and practice.

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Chapter 1

What Makes Human Resource Information Successful?

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Abstract

Human resource information (HRI) is information such as head count, fluctuation, succession planning or results from employee surveys that is available to an organization. Despite being a high priority issue for practitioners and researchers, this topic remains far from reaching a level at which the users of HRI – mostly managers and senior executives – are satisfied and perceive HRI as effective and useful for decision-making. This is due to a knowledge gap regarding which relevant attributes HRI needs to hold. In order to fill this gap, we built on theoretical arguments from the information systems literature and integrated them into an HRI success model with the key variables ease of use, information quality, perceived usefulness, user information satisfaction, and information use. This model was tested among 179 managers in Swiss banks, and structural equation modeling provided clear support for it. In particular, information quality was a key determining factor for both user information satisfaction and information use, and there was a weak link between user information satisfaction and actual HRI use. Both academia and practitioners might benefit from this model by achieving a deeper understanding of the key factors and interdependencies leading to successful HRI.

Introduction

Increasing competition, narrowed talent markets, aging workforces, and a shift towards knowledge-based work are forcing organizations to set a higher priority on improving workforce productivity. One way to improve workforce productivity is to make better decisions regarding human resources. Therefore, decisions about human resources and organizational effectiveness are becoming increasingly vital to the strategic success of virtually all organizations (Cascio & Boudreau, 2008). Good decisions, in turn, are based on valuable information, in this case human resource information (HRI), which can be defined as all information concerning an organization's human resources such as head count, fluctuation, composition of talent pools, use and effectiveness of training and development initiatives, results from employee surveys, performance management, utility analysis, succession planning, age distributions and other forms of workforce-related information (Lawler, 2008).

The increased demand for reliable and useful HRI has pushed the subject to the top of the practitioners' agenda: A recent survey asked HR professionals from numerous industries, geographies and sizes for their top ten priorities for 2008, and found that selecting and monitoring high-impact HR performance indicators was ranked as a top priority by over 37% of respondents and ranked third place out of ten overall (CLC, 2008). Accordingly, consulting firms are offering an increasing amount of advice and products designed to measure HR activity with the aim of providing useful information to decision makers (McKinsey: Harmon, Hensel, & Lukes, 2006; IBM: Lesser & DeMarco, 2006, and IBM, 2007; PWC, 2006). Furthermore, a number of companies have developed human resource metrics databases and benchmarking tools to facilitate strategic decision-making for practitioners (e.g., Saratoga, 2007).

An important topic in this field is the measurement of HRI. Researchers from disciplines as diverse as accounting (e.g., Echols, 2005), finance (e.g., Bryan, 2007), and operations management (e.g., Schneider, 2006) compete to define the latest indicators for human resources within organizations (Boudreau & Ramstad, 2007). The "metrics challenge" (Huselid, Becker, & Beatty, 2005, p. 63) is addressed in a variety of books, proposing a universe of HR indicators and strategies to face managers' need for valuable HRI (Boudreau & Ramstad, 2007; Cascio & Boudreau, 2008).

Despite this considerable effort and development in academia and practice, there seems to be a considerable gap in both worlds: In academia, there is no study known to us that outlines the fundamental principles and variables that lead to successful HRI. Such a framework is necessary to understand the needs and cognitive processes of the users of HRI, to guide theoretical development and to allow for its empirical testing. In practice, there are reasons to doubt the usefulness and effectiveness of the existing approaches to HRI: For example, the "IBM Global Human Capital Study 2008", which held structured interviews with more than 400 HR executives from 40 countries, revealed that only 6% of companies interviewed felt that they were very effective at using human resource data and information to make decisions about their workforce (IBM, 2007). Additionally, Lawler, Boudreau, and Mohrman (2006) surveyed the HR executives of 100 large corporations and found that they reach only low levels in assessing and improving the human resource strategy with their existing HRI. Similarly, Weiss and Finn (2005) surveyed 246 CEOs, Managing Directors and senior HR professionals in Canada and the UK, and found out that organizations are not currently focusing on the measures that were considered to count, resulting in a low usefulness of the available HRI for strategic decision-

making. In other words, the effectiveness of the existing approaches to HRI seems to be very low (Lawler, 2008).

Thus, a critical question that needs to be asked is: What are the relevant attributes that HRI needs to hold in order to be valuable for organizational decision makers, with the term "valuable" referring to its ability to improve vital decisions about human resources (Cascio & Boudreau, 2008)? As Stanton and Coovert (2004) stated, it is important to tackle such a question in order to ensure a positive, extensible role for HR in the information-based organization. Without having a clear understanding of the variables that determine the value of HRI, the tremendous effort undertaken by practitioners and academics is running the risk of missing its main target, which is the improvement of decisions about human resources. This question appears to be even more important in light of the fact that it has been left answered in past decades, resulting in decreased interest in available solutions such as utility analysis (Boudreau & Ramstad, 2003; Choragwicka & Janta, 2008). As to our knowledge, no study in the field of HRM has developed a theoretical framework to investigate the attributes of valuable HRI, we present a model of HRI success that answers this question. Additionally, we test this model's empirical accuracy in order to define the basic principles and thus guide further practical and theoretical development in the field of HRI. We build upon a well-established model in the field of information systems (IS). This allows (a) the concept of HRI success factors to be theoretically bolstered with the well-developed research stream of IS literature, (b) the identification of the relevant variables related to user satisfaction with HRI and HRI usage, and (c) the interlinkages of these variables among each other to be explored. Furthermore, we move from correlations and regression analysis, as used by previous authors in the field (Haines &

Petit, 1997; Voermans & Van Veldhoven, 2007), to structural equation modeling (SEM), which allows us to analyze data at the construct level and to consider error variance.

HRI Success Model

To face the challenge of presenting valuable and reliable HRI to decision makers, many large corporations have some computer-based HRI system in place (Fisher & Howell, 2004). Computer-based HRI systems relieve HR professionals of many routine paper-handling tasks so that they can develop a stronger service orientation and participate more fully in strategic decision-making (Duff, 1989). Beyond these rather administrative tasks, computer-based HRI systems can support recruitment, selection, hiring, job placement, performance appraisals, employee benefit analysis, training development, health, safety and security (Boudreau & Ramstad, 2007). In this way, information technology is used to improve decision-making and support competitiveness (Haines & Petit, 1997; Hussain, Wallace, & Cornelius, 2007). This indicates that the subject of HRI is nowadays closely tied to that of IS. (However, it should be noted that commonly, not all aspects of HRI are stored in a computer-based HRI system because, e.g., the cost-benefit ratio involved in putting certain HRI aspects into a computer-based HRI system is too low.)

In the IS field, the Technology Acceptance Model (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989) constitutes the most prominent theoretical framework. This model was designed to generally predict information technology acceptance and usage. It has predominantly been used in the IS literature to examine user reactions to information systems (Wixom & Todd, 2005) and has been widely applied to a diverse set of technologies and users. Researchers have replicated the basic findings of this model in many situations, with some minor modifications

and extensions (e.g., Davis & Venkatesh, 1996; Horton, Buck, Waterson, & Clegg, 2001; Mathieson, 1991; Rai, Lang, & Welker, 2002; Sabherwal, Jeyaraj, & Chowa, 2006; Seddon, 1997; Taylor & Todd, 1995; Venkatesh, Morris, Davis, & Davis, 2003).

The Technology Acceptance Model explains interrelationships among five key constructs. These constructs are ease of use, information quality, perceived usefulness, user information satisfaction, and information use. These variables can be assigned to three classes of variables: measures of beliefs about information systems (ease of use and information quality), measures of attitudes about using an information system (perceived usefulness and user satisfaction with information), and behavior (information system use). According to the Technology Acceptance Model, beliefs are expected to impact attitudes, and in turn, attitudes are expected to impact behavior (Davis, 1989; Rai et al., 2002; Wixom & Todd, 2005).

Given that HRI is often made available by means of a computer-based HRI system, it is possible to tailor the Technology Acceptance Model to the question of what relevant attributes HRI needs to hold in order to be valuable for organizational decision makers, because if this model generally explains what a valuable information system is, it should also do so for HRI as a special case of information system. Interestingly, the possibility of tailoring the Technology Acceptance Model to the HRI field has already been mentioned (Fisher & Howell, 2004; Voermans & Van Veldhoven, 2007), but it has not been empirically tested in its entirety within the HRI context. As stated above, such a tailoring should take into account that HRI does not need to be stored in a computer-based HRI system, because it can also be stored in paper version, or is only known to some individuals in an organization without any systematic storage. Thus, if the goal is to examine what attributes valuable HRI needs to have, the focus should not be restricted to computer-based HRI, but should rather be on all sorts of HRI available to managers.

Figure 1 depicts the proposed relationships among the constructs related to HRI success based on the Technology Acceptance Model. We will elaborate on all hypotheses below.

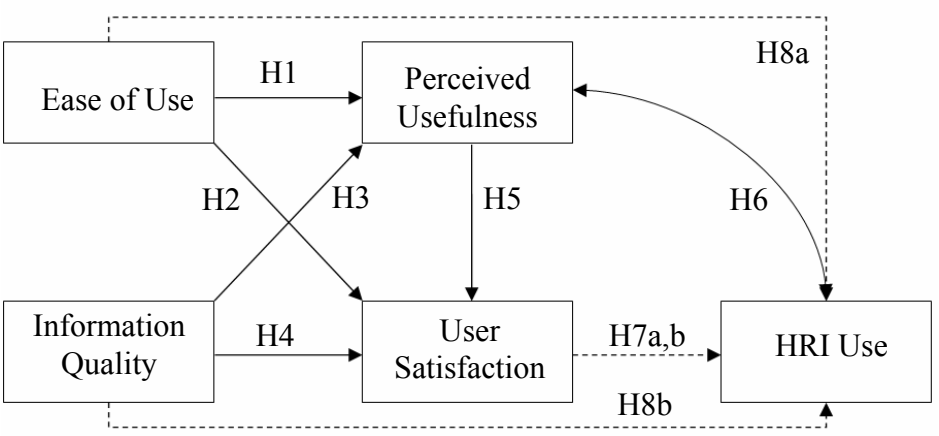

Figure 1. Human resource information (HRI) success model and its hypotheses H1 to H8b (dotted lines represent findings of the Sabherwal et al. 2006 meta-analysis).

Ease of use refers to "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). According to the Technology Acceptance Model, an application that is perceived to be easy to use is more likely to be accepted by users (Davis, 1989). Therefore, if HRI is easy to use, it is likely to be perceived as useful and users should be more satisfied (i.e., a subjective evaluation of HRI as pleasant, Seddon, 1997). Some supporting evidence comes from the exploratory study by Haines and Petit (1997), which focused on computer-based HRI systems. Although their study was not based on the Technology Acceptance Model, it did include ease of use as an explanatory variable for satisfaction with information, and the authors found that ease of use significantly predicted satisfaction with HRI.

Additionally, Voermans and Veldhoven (2007) investigated attitudes and found significant correlations between ease of use and perceived usefulness, and between ease of use and attitudes towards computer-based HRI systems. In the IS literature, both Seddon (1997) and Rai et al. (2002) found that ease of use was a significant predictor of perceived usefulness and satisfaction with information. The meta-analytic results of Sabherwal et al. (2006) supported this finding, as ease of use had a significant impact on user satisfaction and perceived usefulness. Additionally, the recent and extensive literature review by Petter, DeLone, and McLean (2008) showed support for relationships between ease of use and perceived usefulness and information satisfaction, respectively. Based on this logic and previous findings, we formulate the following hypotheses:

H1: Ease of use will be a predictor of perceived usefulness of the available HRI.

H2: Ease of use will be a predictor of information satisfaction.

Information quality describes the degree to which information has attributes such as accuracy, reliability and content required by the user (Davis, 1989; Rai et al., 2002). Doll and Torkzadeh (1988) studied content, accuracy, and format as separate constructs and found high pairwise correlations among the three constructs, such that they were treated as a single-factor construct in subsequent studies (Rai et al., 2002). Although information quality was not explicitly considered in the original Technology Acceptance Model, recent extensions of this model have included information quality as a belief variable (DeLone & McLean, 1992; Rai et al., 2002; Seddon, 1997). The characteristics of information quality represent some of the most extensively studied attributes of information in the IS research literature (e.g., Bailey & Pearson,

1983; Baroudi & Orlikowski, 1988; Magal, 1991; Myers, Kappelman, & Prybutok, 1997; Rainer & Watson, 1995; Seddon & Yip, 1992). If HRI contains precise, decision-relevant information as measured with information quality, it is likely to be perceived as useful and users will be more satisfied. Meta-analytic results from Sabherwal et al. (2006) as well as the literature review by Petter et al. (2008) support this view. Therefore, we formulate the following hypotheses:

H3: Information quality will be a predictor of perceived usefulness of the available HRI.

H4: Information quality will be a predictor of user information satisfaction.

Perceived usefulness is supposed to be a perceptual indicator of the degree to which a person believes that using particular information can enhance his or her job performance (Seddon, 1997). In the HRI context, information is useful if it produces benefits – if HRI improves important decisions in an uncertain world (Bazerman, 2002; Bierman, Bonini, & Hausman, 1991; Boudreau & Ramstad, 2003). Perceived usefulness is expected to facilitate user information satisfaction (Rai et al., 2002; Wixom & Todd, 2005). In other words, if a user perceives the available HRI as influencing his or her decisions in a positive way and as improving performance, he or she is more likely to be satisfied with the available HRI. This relationship has proved to be consistent across a wide variety of IS-related studies (e.g., Petter et al., 2008; Rai et al., 2002), as well as in the context of computer-based HRI systems (Voermans & Van Veldhoven, 2007). Therefore, we hypothesize:

H5: Perceived usefulness will be a predictor of user information satisfaction.

Additionally, it is argued in the original Technology Acceptance Model (Davis, 1989) that perceived usefulness influences HRI use. However, other authors (e.g., Rai et al., 2002) argued that perceived usefulness and system use might function in a bidirectional manner, as perceived usefulness on the one hand affects system use (on two paths, meaning one direct path and one indirect path through information satisfaction) and on the other hand, information use in turn provides feedback regarding perceived usefulness. This was taken into account by Rai et al. (2002), who included a correlational connection between perceived usefulness and system use (Rai et al., 2002). This correlation reflects the assumption that an IS that is high in perceived usefulness is one for which a user believes in a positive use-performance relationship (Davis, 1989). This hypothesis was supported in the Ray et al. (2002) study and received additional confirmation by the meta-analysis of Sabherwal et al. (2006). Furthermore, this bidirectional view also gained support from the literature review by Petter et al. (2008), in which support for both directions was found. Therefore, we hypothesize:

H6: Perceived usefulness will be correlated with HRI use.

Many previous studies implied a causal path from user satisfaction to IS use (e.g., Venkatesh et al., 2003), based on the argument that system use depends on the users' evaluation of that system, meaning that if the system increases the users' decision quality or performance, they tend to use the system (Bokhari, 2005). However, different studies have found a weak or non-existent link between these two variables, and Wixom and Todd (2005, p. 85) concluded that "[u]ser satisfaction is a weak predictor of system usage". This assumption is consistent with the findings of Haines and Petit (1997) in the context of computer-based HRI systems. In his

recent meta-analysis, Bokhari (2005) found that a significant positive, albeit not very strong, relationship between user satisfaction and system use exists. The meta-analytic findings by Sabherwal et al. (2006) concluded that there might be no relation between these two variables. As there is a lack of consensus among previous studies regarding whether user satisfaction and information use are connected (Petter et al., 2008), we formulate two alternative hypotheses:

H7a: User satisfaction will be a predictor of HRI use.

H7b: User satisfaction will not be a predictor of HRI use.

Mawhinney and Lederer (1990) reasoned that users who perceive a computer-based HRI system as easy to use are expected to use the system to a greater extent. In turn, an HRI system that is difficult to use, for example as it is inflexible and hard to learn and understand, cannot be expected to be used frequently (Haines & Petit, 1997). In their meta-analysis, Sabherwal et al. (2006) found confirmation for this path pointing from system quality (in their study composed of information quality and ease of use) to system use. Furthermore, ease of use and information quality were also depicted as affecting IS use in the DeLone and McLean model of IS success, which is a parent model of the model used in our study. This leads to our final hypotheses:

H8a: Ease of use will be a predictor of HRI use.

H8b: Information quality will be a predictor of HRI use.

Method

Sample

In order to achieve a homogenous sample in terms of industry, we surveyed executive bank managers in the German-speaking area of Switzerland over a period of three months. Banks were chosen as they are typical service companies that heavily rely on their employees and are therefore considered a "people business" (Fischer & Mittorp, 2002) that depends on valuable HRI. We focused on executive managers as respondents because they are usually the users of HRI. We approached senior HR Business Partners within the target banks in order to retrieve email addresses of potentially participating line managers and contacted them directly via email. We offered to create a bank-specific report on the model variables as an incentive. Additionally, we recruited managers of banks via an internet platform called Xing (www.xing.com). Xing is an internet portal for professional business networking, focusing on businesspeople worldwide. In September 2007, the Xing community consisted of 4.25 million members worldwide. We sent an invitation email to all targeted individuals outlining the purpose of the study and containing a link to an online questionnaire. We also included a list of examples of what we refer to as HRI, adapted from Lawler (2008).

Out of 418 potential participants approached, 205 (49.0%) reached our online questionnaire. To reduce the potentially negative impact of dropout in internet-based research (Bosnjak, 2001), we included a seriousness check (Reips, 2002). In other words, at the beginning of our questionnaire, we asked participants if they were serious about participating in our study, and only included into further analysis the data from participants who agreed to do so. Participants who indicated that they only wanted to have a look at the online questionnaire (n = 23) were removed from further analysis, yielding a sample size of 182 (43.5%) managers.

To ensure that respondents could be called key informants (Chen, Farh, & Macmillan, 1993; Kumar, Stern, & Anderson, 1993), we measured their involvement in HRI-related decisions, i.e. whether they were in a leadership position. To this aim, respondents were asked to indicate how many employees they led. On average, participants led a group of 15 people (*SD* = 23.4). However, three respondents indicated that they did not lead a single employee. In line with key informant methodology (Kumar et al., 1993), these respondents were removed, resulting in a final sample of 179 (42.8%) managers.

This final sample included 94% males and 6% females. Their age ranged from 33 to 58 years, with an average of 46 years (*SD* = 6.0). Three percent of the participants had completed only the compulsory nine years of public schooling. The majority of the participants (45%) went to training school, completing another three to four years of apprenticeship, or to commercial school (28%), with a focus on economic and administrative tasks. A quarter of the participants had a university degree or PhD. The average time in the current position was 3.5 years (*SD* = 1.4). Company size varied substantially in size, with 77% having more than 10,000 employees and 6% having fewer than 1000.

Measures

To adequately capture the variables, we relied on the items provided by Rai et al. (2002). We adapted these items to the context of HRI by replacing the computer-focused component of IS with the somewhat broader term of HRI. All items refer to the individual rather than to the organizational level. After pre-testing the data on a preliminary sample of managers of Swiss banks (*N* = 43), we adjusted some of the original scales by dropping items that lowered the

internal consistency of the respective scale. All items were answered on a 5-point scale (1 = strongly disagree, 5 = strongly agree) unless otherwise indicated.

Ease of Use. We adapted the scale presented by Rai al. (2002) to measure ease of use consisting of two items ("The HRI available is user friendly" and "The HRI available is easy to use"; Cronbach's alpha = .86).

Information Quality. We adapted the Rai al. (2002) information quality scale, referring to the degree to which information has attributes like accuracy, reliability and content required by the user. Because two of the original items were strictly focused on information quality of computer-based IS, we dropped these items, thus reducing the original seven-item scale to five items. One of these five items was found to decrease the reliability in our pre-test and was dropped. Thus, we used the following items: "The HRI available is sufficient to enable me to do my tasks", "The HRI available is the precise information I need", "The HRI available is exactly what I need to make workforce-related decisions", and "I am satisfied with the accuracy of the HRI available" (Cronbach's alpha = .82).

As Sabherwal et al. (2006) combined the information quality and ease of use construct into one scale ("system quality"), we tested whether combining the items of information quality and ease of use into one latent variable would be adequate by performing a confirmatory factor analysis using the AMOS software package (Arbuckle, 2005). We used the root mean square error of approximation (RMSEA, which should be < .08), the non-normed fit index (NNFI), the comparative fit index (CFI), and the incremental fit index (IFI, with the NNFI, the CFI, and the IFI ideally being >.90, Browne & Cudeck, 1989; Hoyle, 1995). A measurement model with only one latent variable showed an unacceptable fit (RMSEA = .261, NNFI = .390, CFI =.739, IFI = .747), which was significantly lower (χ^2 (1) = 100.3, p < .001) than a model that treated both

dimensions separately (RMSEA = .000, NNFI = 1.03, CFI =1.00, IFI = 1.00; thus a model with an excellent fit). Therefore, in line with Rai et al. (2002), we kept these two dimensions separate.

Perceived Usefulness. The items were: "Using HRI improves my job performance", "I find HRI useful on my job", "Using HRI enables me to make leadership decisions more easily", "Using HRI makes it easier to do my job as a manager", and "Using HRI in my job increases my productivity as a manager". Due to reliability considerations, we dropped one of the original items provided by Rai et al. (2002) after pre-testing the scale, leading to a Cronbach's alpha of .91.

User Information Satisfaction. Rai et al. (2002), who used a one-item omnibus measure for measuring the satisfaction with information ("How would you rate your satisfaction with the IS?"), suggested using this measure if a global interest in capturing user satisfaction exists. This suggestion was also made by Baroudi and Orlikowski (1988), who concluded from their empirical analyses that a single-item measure of user satisfaction can be used when an overall indication of user information satisfaction is desired. Furthermore, within the context of industrial and organizational psychology, single-item indicators of job satisfaction show strong convergent validity with job satisfaction scales and are considered to be more robust than the scale measures of overall job satisfaction and therefore acceptable (Wanous & Hudy, 2001; Wanous, Reichers, & Hudy, 1997). Due to these arguments and owing to concerns about survey length, we used a single item to measure user information satisfaction and adapted the item suggested by Rai et al. (2001) to the HRI context ("How would you rate your satisfaction with the HRI available?").

Information Use was measured with the two information use items from Yang and Yoo (2004): "On average, I use HRI never, less than once a year… several times a week" and

"Overall, I use HRI never, very seldom … very often", augmented by an item from Rai et al. (2002) ("I depend on HRI", Cronbach's alpha = .82).

Strategy of Analysis

In order to test the HRI success model, we performed structural equation modeling analyses. To assess model fit, we took our hypothesized model as a starting position. Apart from this model, we tested two rival models from the IS literature (referred to above), proposing different theoretical relationships between the introduced variables. To compare the fit of the models, χ^2 difference tests were used.

Results

Table 1 shows the means, correlations, and the internal consistencies (Cronbach's alphas) of the measures. As can be seen, the measures showed good to very good reliabilities.

Table 1

Means, Standard Deviations, Internal Consistencies [a] *and Correlations* [b]

Variable	M	SD	1	2	3	4	5
1 Ease of use	2.93	0.93	(.86)				
2 Information quality	3.70	0.68	.42	(.82)			
3 Perceived usefulness	3.40	0.77	.33	.50	(.91)		
4 User satisfaction with information	3.40	0.84	.51	.72	.56	-	
5 Human resource information use	3.47	0.94	.13	.46	.54	.45	(.82)

Note. [a] Cronbach's alphas in the diagonal in parenthesis.

[b] Correlations greater than .19, $p < 0.01$; Correlations greater than .14, $p < .05$; (2-tailed significance).

Our HRI use scale included the question "On average, I use human resource information "never" to "several times a week". The results of this particular item ($M = 3.73$, $SD = 1.17$, not indicated separately in Table 1) indicated that managers used HRI on average between once every six months (item answer = 3) and once a month (item answer = 4).

Test of the HRI Success Model

The first model equals our proposed HRI success model as outlined in Figure 1. This model tests our hypotheses H1 to H7a and H8a and H8b. The fit indices of this model lie within the recommended quality criteria of SEMs, indicating acceptable model fit (see Table 2).

Table 2

Results of Structural Equation Modeling: Fit Indices of the Hypothesized Human Resource Information (HRI) Success Model, the Final HRI Success Model, and the two Rival Models

Model	χ^2 (N = 179)	*df*	RMSEA	NNFI	CFI	IFI
1. Hypothesized HRI success model	167.6	82	.074	.918	.944	.945
2. Parsimonious and final HRI success model	169.1	84	.072	.920	.944	.945
3. Rival model A: Seddon (1997)	221.3	85	.091	.867	.906	.908
4. Rival model B: Sabherwal et al. (2006)	173.5	85	.073	.913	.939	.940
Null model = independence model	1640.9	105	.275	.	.	.

Note. GFI = goodness-of-fit index; RMSEA = root mean square error of approximation; NNFI = non-normed fit index; CFI = comparative fit index; IFI = incremental fit index.

However, the path coefficient from user information satisfaction to system use as represented by hypothesis H7a did not reach the significance level. Additionally, the path weight from ease of use to HRI was also not significant, thus failing to confirm hypothesis H8a.

The second model represents our parsimonious and final HRI success model, which takes into account the findings from model 1, omitting both the path from user satisfaction to HRI use and the path from ease of use to HRI use (see Figure 2). Testing this model resulted in a slightly improved model fit, as shown in Table 2. However, this improvement was not statistically significant ($\Delta\chi^2$ (2) = 1.5, $p < .47$), although all path coefficients are significant and in the expected direction. These results support our hypotheses H1 to H5 and H8b. Moreover, hypothesis H6, which asserted a significant correlational link between perceived usefulness and system use, can also be accepted. As the path coefficient from user information satisfaction to system use did not reach the significance level, we rejected hypothesis H7a and accepted hypothesis H7b, which claimed that user satisfaction is not a predictor of HRI use.

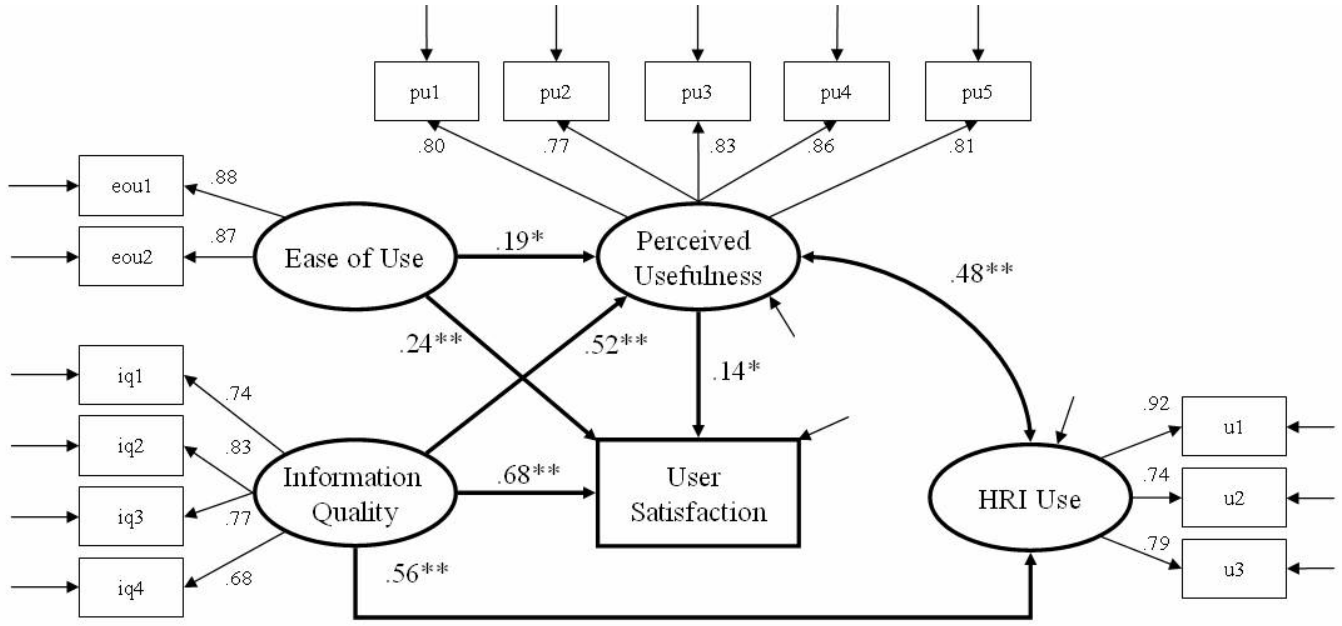

Figure 2. Empirical results for the parsimonious and final human resource information (HRI) success model (eou = observed variables for ease of use; iq = observed variables for information quality; pu = observed variables for perceived usefulness; u = observed variables for HRI use).

In addition to this parsimonious and final HRI success model, we tested two rival models from the IS literature. The first rival model represents a nested model of our initially proposed HRI success model. It was introduced to the IS literature by Seddon (1997), and later on confirmed by Rai et al. (2001), as mentioned above. We chose this model as a first rival model because it conceptually elaborates and clarifies aspects integrated in core theoretical relationships suggested by the IS success literature (Rai et al., 2001). This model does not contain the path from information quality to HRI use and does not assert a correlation between perceived usefulness and HRI use (i.e., it only consists of the hypotheses H1 to H5 and H7a). The fit of this model was worse (see Table 2 under rival model A) and its fit was significantly lower ($\Delta\chi^2(1) = 52.2$, $p < .001$) than our parsimonious and final HRI success model.

The second rival model is the emergent model from the Sabherwal et al. (2006) meta-analysis. We chose this model as a second rival model as it represents one of the most compelling aggregations of findings from the IS literature to date. In this model, information quality is related to perceived usefulness, user satisfaction and HRI use, whereas no connection between perceived usefulness and user satisfaction, and no link between user satisfaction and HRI use is assumed (i.e., it only consists of our hypotheses H1 to H6, H7b, and H8b), and it is also nested in our final HRI success model. Even though the fit of this model was acceptable (see Table 2 under rival model B), it showed a significantly lower model fit ($\Delta\chi^2(1) = 4.4$, $p < .05$) compared to our parsimonious and final HCI success model. In sum, investigation of these two

rival models provides further support for the relationships outlined in our parsimonious and final HCI success model specified in Figure 2.

Discussion

This study outlined a theoretical model that is able to explain which variables are important for users of HRI and how these variables are interlinked. We adapted a theoretical framework from the IS literature and applied it to the context of HRI. Empirical testing of this model resulted in a good model fit and the proposed relationships in the final HRI success model were all significant and in the expected direction, which confirmed this adaptation. Thus, we extended previous research in the field of human resource management by combining the results from earlier studies with further relevant variables and a theoretical framework from the IS success literature. This new theoretical framework can now be used for further investigation of the attributes of valuable HRI and to guide theoretical development in the field of HRI, helping to provide an understanding of users' cognitive processes when evaluating the available HRI.

Our results suggest that the source of HRI may vary, but the variables determining its success might be independent of its source. Whether this information is provided by a sophisticated computer-based HRI system or in simple paper reports, the key attribute which HRI needs to fulfill is that it contains high-quality information required by the user. Thus, HR professionals may not primarily depend on the implementation of an expensive computer-based HRI system or complex analysis software, but rather on accurate and useful information (even if it is well supported by computer-aided systems). Actually, in many cases, the cost-benefit ratio involved in putting certain HRI into a computer-based system might in any case be questionable. In particular, if complex issues are addressed such as connecting human resource practice to

organizational performance (e.g., Lawler, 2008), a great deal of analytical effort has to be undertaken in a first step, and only after some time, when procedures, results and reports are becoming standardized, does the implementation in a computer-aided system make sense.

As organizations are now looking to the HR function in order to reach beyond the delivery of cost-effective administrative services, HR needs to provide expertise on how to leverage human resources and provide the strategic insights that the business requires (Lesser & DeMarco, 2006). Although the quantitative measurement of human resources in order to retrieve valuable HRI is receiving unprecedented attention, the topic is far from satisfying the users needs (Gates, 2008; IBM, 2007; Lawler et al., 2006; Weiss & Finn, 2005). Our results emphasize the importance of the key variables related to HRI success. Consistent with earlier studies in the IS field (see Petter et al., 2008 for an extensive review), we found a significant impact of information quality and ease of use in terms of attitudes towards HRI and use of HRI. For practitioners, our study offers an attractive framework that can be used to identify indicators for improving their own available HRI, as outlined in the next paragraphs.

Improving HRI Success

Increasing perceived usefulness. Perceived usefulness is primarily determined by information quality, while ease of use explains only a relatively small amount of variance. This finding is in line with the results of Voermans and Veldhoven (2007), who found that ease of use correlates with attitudes towards HRI systems, but does not contribute in a significant way to explaining the variance in attitudes towards HRI systems.

A look at the items related to information quality reveals possible triggers for increasing the amount of information quality and thereby the perceived usefulness of HRI. This shows that

practitioners should aim to find a close relationship between their users' needs and the content provided by the available sources of HRI. In particular regarding the increasing amount of computer-aided analysis tools, the amount of available information is increasing accordingly. The items reveal that it is not the amount of information, but rather the fit between user requirements and the available HRI-related content which drives the perceived usefulness. Ways in which this fit can be increased include extensive communication with the target group of any HRI, structured interviews, critical incident analysis, and focus groups involving line managers from various levels to clarify expectations and needs regarding the content required for making workforce-related decisions.

Increasing user information satisfaction. Like perceived usefulness, user information satisfaction is influenced more by information quality than by ease of use, but ease of use (and perceived usefulness) also explained a significant amount of variance in user information satisfaction. Thus, practitioners should focus on all three influencing variables, namely information quality, ease of use and perceived usefulness, if they wish to increase users' satisfaction with the HRI. However, user satisfaction proved not to directly influence HRI use, indicating that increasing satisfaction should not be the dominant goal for practitioners.

Increasing HRI use. The results showed that HRI use was primarily determined by the perceived information quality and that there was a strong link with the perceived usefulness of the available HRI, whereas we did not find a direct connection between user satisfaction and HRI use. These findings are consistent with those of Haines and Petit (1997) and Sabherwal et al. (2006), and indicate that practitioners who aim to increase HRI use should primarily focus on information quality and perceived usefulness. Although user satisfaction proved not to directly influence HRI use, it still depended on the same variables as HRI use (namely ease of use,

information quality and perceived usefulness). Thus, if practitioners make their HRI easier to use and improve its quality and its usefulness, this should result in higher HRI usage and, as a by-product, also in higher satisfaction with the HRI.

Limitations and Future Research

Measures used in this study were gathered from a single questionnaire, which introduced the possible problem of common method bias, implying that the results may be affected by the measurement process. To address this, we used Harman's one-factor test by including all items from all of the constructs in the study into a confirmatory factor analysis to determine whether the majority of the variance can be accounted for by one general factor (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). This resulted in a very low model fit (RMSEA = .170; CFI = .630, NNFI =. 525, IFI = .637), indicating that common method variance may not be a problem in this study. This is in line with arguments claiming that concerns about common method variance are likely to be overstated (Spector, 2006).

Nevertheless, we suggest that future studies could focus on other output-oriented measures such as improved decision-making (Boudreau & Ramstad, 2003), or better products and services or cost savings, rather than the use of computer-based HRI systems. Future research should also incorporate other dependent variables like success measures that refer not only to use, but also to the quality, individual impacts and organizational impacts of information systems (see Bergeron, Raymond, Rivard, & Gara, 1995) or user reactions, such as the interpretation of corporate values and goals, and sabotage (see Fisher & Howell, 2004).

Given that our sample consisted of managers working in Swiss Banks, the generalization of our findings to other settings may only be possible within the service-oriented industry, as

Swiss Banks are typical service providers relying heavily on human resources. Whether our findings apply to other settings such as the manufacturing industry is unclear and could be the subject of further research endeavors.

The questionnaire used in this study has proven to be a reliable tool in the assessment of HRI attributes. For this reason, and because each of the constructs used in our model is covered by a rich item pool, it could be used in many organizational contexts. In this way, the instrument might become a useful diagnostic tool for internal and external benchmarking and to detect problems within a company's available HRI. We would like to encourage other practitioners to use our questionnaire further and to share their results. Over the years, and by spreading across different industries, this could provide a benchmark for companies to assess their individual HRI success index.

Conclusions

Writers from the areas of business, academia, and public policy have noted that business decisions need to happen more quickly, and at the same time, these decisions are increasingly dependent on human resources and its organization (Boudreau & Ramstad, 2007). Researchers have developed an increasing number of new indicators in recent years, attempting to quantify the value of human resources and provide adequate information to decision makers (Bryan, 2007; Bukowitz, Williams, & Mactas, 2004; Fitz-enz, 2000; Schneider, 2006). The current findings add to this growing body of literature on HRI by depicting some of the basic principles that are vital for the success of such indicators. This study has shown that for the providers of HRI, it is essential to keep a constant eye on the ease of use, the decision relevance and the congruence between users' information requirements and the HRI provided. If HR intends to

provide true expertise on how to leverage human resources and provide the strategic insights which the business requires, a stronger focus must be set on the identified attributes. Otherwise, the tremendous effort that is being put into turning HR departments into more strategically positioned organizational units may fail.

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Chapter 2

Causal Chain Analysis as an Alternative to Single-Attribute Utility Analysis

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Abstract

Research on providing single-attribute utility analysis has shown moderate or even negative effects on the acceptance of selection and training tests by human resource decision makers. In the present study, we contrasted single-attribute utility analysis with causal chain analysis as an alternative way of conducting utility analysis. Causal chain analysis focuses on measuring the linkages between HRM interventions and organizational outcomes mediated by employee attitudes and customer perceptions. We compared 144 mangers' reactions to both methods of utility analysis using the human resource information success model, which explains the success of human resource information through the variables understandability, information quality, perceived usefulness, user information satisfaction, and intention to use. Causal chain analysis yielded higher results than single-attribute analysis for these variables. A mediation analysis provided an explanation of why these effects occurred: The effect of a given utility analysis method on intention to use and information satisfaction is simultaneously mediated by understandability and information quality. This indicates that causal chain analysis is a powerful alternative of communicating the utility of HRM interventions.

Introduction

More than ever before, human resource practitioners have to show a connection between their interventions and organizational performance (Cascio & Boudreau, 2008). In the context of personnel selection, performance management, and development, this means that measures showing a direct relation to strategic business goals will likely be favored by organizational decision makers (Cascio, 2000). Hence, HR departments are under pressure to continuously produce documentation for the effectiveness and efficiency of HRM (Morrow, Jarrett, & Rupinski, 1997).

Due to such pressure, HR professionals continue to search for metrics and methods that are able to demonstrate the benefits of their work (Boudreau & Ramstad, 2007; Cascio & Boudreau, 2008; Lawler, 2008; Wintermantel & Mattimore, 1997). Although organizational decision makers have many tools to define how they will use, analyze, and interpret data to demonstrate such impact, utility analysis is arguably considered to be the most important, as "utility analysis is inextricably connected to strategic human capital research" (Boudreau & Ramstad, 2003, p. 215). Utility analysis, in general, describes a wide array of approaches estimating the payoff from HRM interventions such as selection, performance management, and training initiatives (Boudreau, 1990; Boudreau & Ramstad, 2003; Cascio & Boudreau, 2008; Latham & Whyte, 1994; Macan & Foster, 2004; Macan & Highhouse, 1994; Rowold & Mönninghoff, 2005). Utility analysis is intended to provide managers with a basis for deciding whether to invest in HRM interventions. It lends credibility to perceived "soft" decisions commonly associated with HRM (Cascio, 2000; Sturmann, 2000).

Single-attribute utility analysis is the most established form of utility analysis (e.g., Brogden, 1949; Choragwicka & Janta, 2008; Cronbach & Gleser, 1965). It calculates the benefit of an HRM intervention based on a multiplicative combination of factors related to the quality, quantity, and costs of an HRM intervention (Macan & Foster, 2004). Nevertheless,

results from a large number of studies with managers have repeatedly shown levels of acceptance ratings that are "disappointingly low" (Carson, Becker, & Henderson, 1997, p. 84). Consequently, I/O psychology journals have begun to pay less attention to utility analysis (Boudreau & Ramstad, 2003). A recent literature review showed that academic interest in utility analysis has diminished (Cascio & Aguinis, 2008). This may in part be due to Latham and Whyte's (1994) conclusion that single-attribute utility analysis is futile (Latham & Whyte, 1994), which is even the case when an expert explains its benefits to managers (Whyte & Latham, 1997).

An alternative to single-attribute utility analysis is causal chain analysis. Causal chain analysis incorporates outcomes such as company performance, organizational training costs, and customer perceptions. It maps important linking elements (Cascio & Boudreau, 2008). Moreover, it includes multiple, financial and non-financial indicators of success (Cabrera & Raju, 2001; Kaplan & Norton, 1992). Currently, there is no empirical evidence that causal chain analysis is superior to other forms of utility analysis, but only anecdotal evidence that it is very appealing to organizational decision makers (Lawler, Levenson, & Boudreau, 2004; Subramony, 2006). Thus, the purpose of the present study was to compare single-attribute utility analysis with causal chain analysis in terms of its success variables. In the following, we explain both forms of utility analysis in greater detail.

Single-Attribute Utility Analysis

Single-attribute utility analysis is based on the multiplicative combination of several components (e.g., the standard deviation of job performance expressed in monetary units, the validity of the HRM intervention, the number of participants) related to a specific selection, performance management, or training program. The benefit of such an HRM intervention increases proportionally to these parameters. To determine its utility, the expenses of the

intervention are subtracted from the return (Macan & Foster, 2004) using the following equation: utility analysis = (quantity × quality) – costs. Quantity equals the total number of employees affected by an intervention; quality equals the average return of the intervention in terms of a monetary value; and cost is the total cost of the intervention (Boudreau, 1991; Cascio, 1994; Macan & Foster, 2004). The basic equations of single-attribute utility analysis were developed by Brogden (1949) and refined by Cronbach and Gleser (1965) in the context of personal selection:

$$\Delta U = T * N * Z_x * r * SD_y - C \quad (1)$$

ΔU = Utility change from selection device

T = Average tenure of hired people

N = Number of people to be hired

Z_x = Average Z-score of the predictor of hired employees

r = Correlation between a predictor and criterion

SD_y = Monetary value of standard deviation in the criterion

C = Cost of acquiring and administering a selection battery

Although it was originally used to estimate the value of selection tests (e.g., Carson et al., 1997; Latham & Whyte, 1994; Macan & Foster, 2004), it was expanded to a broad range of HRM interventions from the 1990s onwards. For example, the utility of a training intervention was assessed as follows (e.g., Cascio & Boudreau, 2008; Hazer & Highhouse, 1997; Mattson, 2003):

$$\Delta U = (dt \times SD_y \times T - C) \times N \quad (2)$$

ΔU = Utility change from a training program

dt = Effect size, reflecting how different those who participate in a development program are in terms of job-relevant outcomes, compared to those who do not participate

SD_y = Standard deviation of the monetary value of job performance among untrained employees

T = Expected duration of benefits of a trained employee

C = Total cost of training per employee

N = Number of trained people

Single-attribute utility analysis models have evoked some controversy, particularly regarding the estimation of the monetary value of the standard performance increment (i.e., SD_y; see e.g., Hazer & Highhouse, 1997). The following three estimation methods have received the most attention: the subjective estimation of SD_y by supervisors (Schmidt, Hunter, McKenzie, & Muldrow, 1979), multiplying the average salary in a job by some proportion, for example 40%; (Schmidt, Hunter, & Pearlman, 1982), and the Cascio-Ramos (1986) estimate of performance in monetary values (CREPID). CREPID involves partitioning annual salary among a job's principal activities so that each activity is assigned a portion of the salary equal to its importance weighting in the job analysis. However, with a large sample of judges, all three methods produce similar results (Schmidt & Klimoski, 1997). Thus, it appears that the methodology of SD_y estimation is not a key factor leading to a positive evaluation of a utility method (see also Hazer & Highhouse, 1997).

SD_y and the subjective judgments for determining it are frequently questioned by practitioners (Wintermantel & Mattimore, 1997). Beyond that, single-attribute utility analysis is perceived as too complex (Macan & Highhouse, 1994). Worse still, the monetary estimates derived from these models are often so overwhelmingly large that managers become skeptical

about the results and, therefore, the method used to obtain them (Cascio & Boudreau, 2008; Latham & Whyte, 1994).

Explanation of Causal Chain Analysis

Causal chain analysis is an alternative method of utility analysis that focuses on measuring the linkages among HRM interventions and organizational outcomes (such as profitability) mediated by employee attitudes and customer perceptions (Boudreau & Ramstad, 2003, 2007; Cascio & Boudreau, 2008). It communicates utility analysis information in the form of causal path models (Subramony, 2006). Sears, Roebuck & Co. used this method to collect data from store associates, their on-the-job behaviors, the responses of store customers, and the financial performance of the stores (Rucci, Kirn, & Quinn, 1998). Based on these connections, the company determined what drove its profit and then derived suggestions for actions that led to long-term profitability (Heskett, Jones, Loveman, Sasser, & Schlesinger, 1994).

Although different causal chain models exist, the common feature is that they calculate path models linking HRM initiatives to employee attitudes, customer perceptions, and profit (Cascio & Boudreau, 2008; Subramony, 2006). The dependent and mediating variables are always the ones mentioned above. Figure 1 summarizes the basic assumptions of causal chain analysis models, based on models suggested by many authors (e.g., Boselie, Dietz, & Boon, 2005; Combs, Liu, Hall, & Ketchen, 2006; Paauwe & Boselie, 2005; Purcell & Hutchinson, 2007) and confirmed in several fields, including industrial and organizational psychology (Gelade & Ivery, 2003; Gelade & Young, 2005; Macduffie, 1995; Paul & Anantharaman, 2003), management sciences (Heskett et al., 1994), operations management (Kassinis & Soteriou, 2003), and marketing (Kamakura, Mittal, de Rosa, & Mazzon, 2002; Lariviere, 2008; Pritchard & Silvestro, 2005; Silvestro & Cross, 2000).

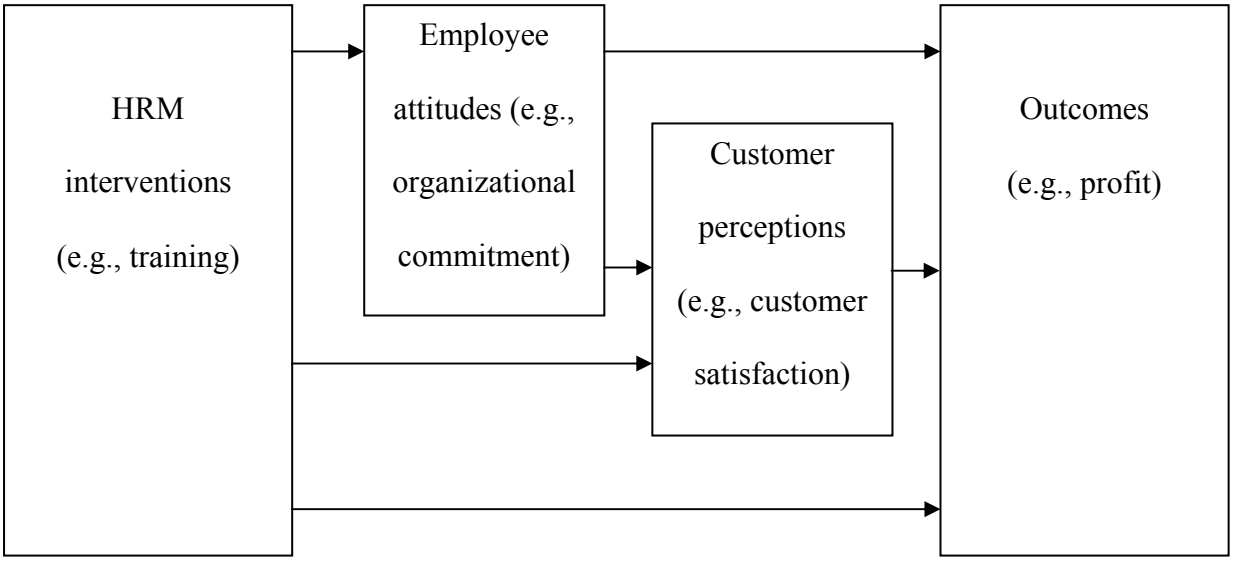

Figure 1. Basic assumptions of the causal chain analysis approach to utility analysis.

Building the database for a causal chain analysis typically requires data from various departments within a company. Data on a specific HRM intervention represent the predictor variable (Boudreau & Ramstad, 2003), such as the percentage of staff who participated in a training program to increase customer service qualification (Gelade & Ivery, 2003). Further requirements are employee attitude surveys (Schneider, Ashworth, Higgs, & Carr, 1996), data on the customers' perception of the service quality that may stem from the marketing department (Brown & Lam, 2008; Kamakura et al., 2002), and financial performance data from the financial controlling department. Path coefficients are typically calculated to give an indication of what the expected outcome in a criterion variable will be, based on a given change in the predictor variable (Cascio & Boudreau, 2008; Gelade & Ivery, 2003; Gelade & Young, 2005; Mirvis & Lawler, 1977, 1983).

Comparing Single-Attribute Utility Analysis to Causal Chain Analysis

Single-attribute utility analysis and causal chain analysis both predict a monetary estimate of the pay-off of an HRM intervention, and both methodologies have the ultimate goal of influencing decisions (Cascio & Boudreau, 2008). However, only causal chain

analysis (a) is presented as a graphical representation of causal paths, (b) incorporates intervening variables (i.e., customer satisfaction and employee attitudes), and (c) presents result information that goes beyond a single final monetary value (i.e., a percentage improvement in the mediating and the target variables).

As utility analysis research has so far been described as being rather atheoretical (Roth, Bobko & Babon, 2001; Boudreau & Ramstad, 2003), we embed the topic into the theoretical framework of human resource information success (Winkler, König, & Kleinmann, 2009). The human resource information success model (Winkler et al., 2009) outlines five constructs related to the success of HRM decision aid tools and is an adaptation of the Technology Acceptance Model (see also, Davis, 1989; Davis, Bagozzi, & Warshaw, 1989) in the information systems field. The success of human resource information is explained in terms of the following five key variables: (a) managers' perceptions of the ease of use, and the clarity of the HRM information presented (Davis, 1989; Mattson, 2003); (b) quality as defined by perceptions of accuracy, reliability and required content (see also, Davis, 1989; Rai, Lang, & Welker, 2002); (c) usefulness as defined by the belief that the human resource information will enhance job performance (Seddon, 1997); (d) satisfaction with a given piece of information (Rai et al., 2002), and (e) use as defined by a user's actual behavior in terms of using the given information.

The model itself is represented by a path model (depicted in Figure 2). Understandability has a direct causal link to perceived usefulness and user satisfaction. Information quality directly influences perceived usefulness and user satisfaction. In addition, information quality is related to information use. Perceived usefulness has a correlational connection with information use and a direct connection with user satisfaction. Winkler et al. (2009) empirically tested this model with 179 bank managers, and a structural equation model provided clear support for its fit, indicating that the described relationships represent the

underlying pattern within the data accurately. In the following, we describe the key variables related to this model.

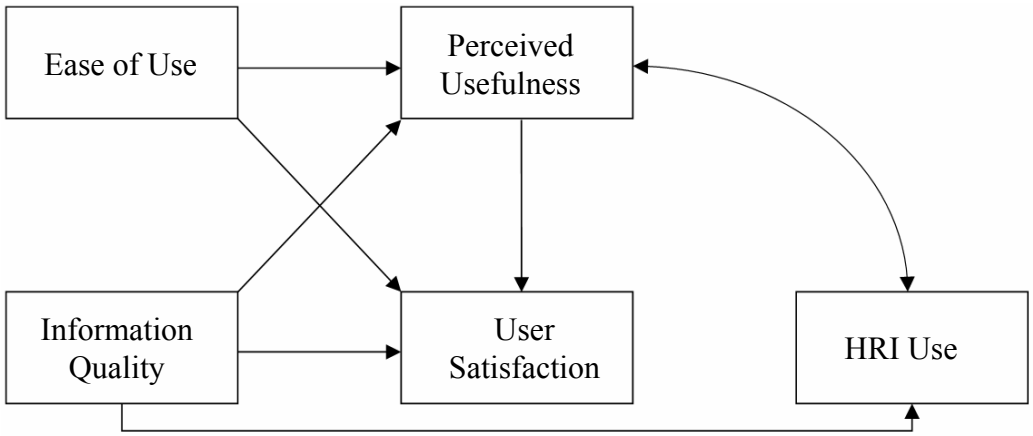

Figure 2. Graphical representation of the paths in the human resource information success model (Winkler et al., 2009). HRI = Human resource information.

Understandability. Carson et al. (1997) examined the effect of different scenarios in the context of single-attribute utility analysis and found that an explanation of single-attribute utility analysis that was shorter and easier to understand yielded slightly more positive effects on managers' reactions. This is associated with another factor that is known to affect managerial decision making, i.e. information complexity (Mattson, 2003). In their general framework for understanding persuasive communications, Cacioppo, Kao, Petty and Rodriguez (1986) hypothesized that increasing the complexity and decreasing the understandability of information increases the likelihood that the information is negatively evaluated by recipients. This indicates that a utility analysis methodology that is easy to understand is likely to generate positive user reactions.

Macan and Highhouse (1994) found that almost one quarter of their respondents felt that the complexity and difficulty of computing, understanding, and explaining utility estimates to management contributed to their lack of use. Causal chain analyses may be easier

to understand by organizational decision makers "because they offer tangible and logical structures and data to understand the intervening links between HR interventions and business outcomes, a feature that is generally lacking in existing utility models" (Boudreau & Ramstad, 2003, p. 203). Furthermore, the graphical representation as well as the outlined intermediating variables (as implemented in causal chain analysis models) may increase the understanding of causal chain analysis.

Hypothesis 1 a): Compared to single-attribute utility analysis, a causal chain analysis receives significantly higher understandability ratings.

Information quality. Macan and Highhouse (1994) found that one third of those participants who have used single-attribute utility analysis found the results to be unbelievable and inaccurate, which are indicators of low information quality (Davis, 1989; Rai et al., 2002). In turn, causal chain analysis enables answers to "what if" questions, based on unstandardized path coefficients (Boudreau & Ramstad, 2003, 2007; Cascio & Boudreau, 2008), a notion that was already mentioned in the context of personal selection by Burke and Pearlman (1988) and Schmidt (1993), who offered percentage improvement in productivity as a potentially valuable means of expressing utility. Together with the result information that goes beyond a single final monetary value, causal chain analysis gives a relatively complete picture of how an HRM intervention influences business performance.

Hypothesis 1 b): Compared to single-attribute utility analysis, a causal chain analysis receives significantly higher information quality ratings.

Perceived usefulness. In the human resource information context, information is useful if it produces benefits such as improved decision making (Boudreau & Ramstad, 2003; Winkler et al., 2009). Both Hazer and Highhouse (1997) and Macan and Highhouse (1994) found that respondents gave single-attribute utility analysis only a medium-rate evaluation in terms of perceived usefulness. Latham (1988) argued that managers are not interested solely in monetary information; they are also interested in variables such as customer satisfaction (Cabrera & Raju, 2001). Causal chain analysis models suggest including variables such as customer perception and employee attitudes, leading to a "[u]seful logic linking employee variables to financial outcomes" (Boudreau & Ramstad, 2003, p. 200).

Hypothesis 1 c): Compared to single-attribute utility analysis, causal chain analysis receives significantly higher perceived usefulness ratings.

Information satisfaction. Little empirical evidence is available for the evaluation of single-attribute utility analysis in terms of an overall evaluation of satisfaction. Nevertheless, Hazer and Highhouse (1994) asked participants for their general impressions of utility estimates, and found that participants who were at least somewhat familiar with single-attribute utility analysis rated the majority of attributes (i.e., accuracy, costliness, credibility, practicality, reasonableness, validity) only at the midpoint of the scale. According to the human resource information success model (Winkler et al., 2009), user information satisfaction is a consequence of the perceived ease of use, the information quality, and the perceived usefulness. Therefore, if causal chain analysis results in higher values in terms of these three antecedents of user information satisfaction, the logical consequence is that causal chain analysis will also yield higher ratings in terms of user information satisfaction.

Hypothesis 1 d): Compared to the single-attribute utility, causal chain analysis receives significantly higher ratings in terms of satisfaction with information.

Intention to use. The human resource information success model includes information use, which is a variable that represents a user's actual behavior. DeLone and McLean (2003) suggested that intention to use might be a worthwhile alternative variable for information use. In our study, intention to use reflects the willingness of a manager to use, encourage and recommend using a given method of utility analysis. We therefore include intention to use as a proxy for the behavioral variable information use.

Managers only occasionally intend to use utility analysis information (Macan & Highhouse, 1994). This might be the case because the methods of utility analysis as well as the modalities of implementation are not sufficiently known by HRM executives and other decision makers in organizations (Cascio & Boudreau, 2008; Macan & Foster, 2004; Sturmann, 2000). This argument is consistent with the experimental finding by Hazer and Highhouse (1997) that a ten-item composite measure, including a five-item "intention to use" facet, led to mid-scale values. Moreover, these ratings were unaffected by the SD_y method, the framing of the information (loss vs. gain), the intervention (training vs. selection) and the participants' comprehension level.

According to the human resource information success model (Winkler et al., 2009), the intention to use the human resource information available is a consequence of the perceived information quality and has a positive correlation with the perceived usefulness. Following this logic, we hypothesize the following:

Hypothesis 1 e): Compared to the single-attribute utility, causal chain analysis receives significantly higher ratings in terms of intention to use.

According to the human resource information success model (Winkler et al., 2009), perceived usefulness and information satisfaction are both affected simultaneously by understandability and information quality. This means that a utility analysis method is more likely to create benefits and lead to higher user satisfaction when it is easy to use and the given information is accurate, reliable and relevant for the user (Winkler et al., 2009). This implies that understandability and information satisfaction should be mediators of the effect of a given utility analysis method on perceived usefulness and information satisfaction.

Hypothesis 2a): The effect of the utility analysis method on perceived usefulness will be simultaneously mediated by understandability and information quality.

Hypothesis 2b): The effect of the utility analysis method on information satisfaction will be simultaneously mediated by understandability and information quality.

The same holds for the intention to use a utility analysis method, as the human resource information success model describes understandability and information quality as preceding variables for information use (Winkler et al., 2009). This is in line with the findings of Macan and Highhouse (1994), who stated that "[a]lmost one-fourth of respondents felt that the complexity and difficulty of computing, understanding, and explaining the estimates to management contributed to their lack of use" (p. 434).

Hypothesis 2c): The effect of the utility analysis method on intention to use will be simultaneously mediated by understandability and information quality.

Method

Sample

Executive managers (n = 660) from the banking sector were surveyed in Germany, Austria, and Switzerland via an internet platform called Xing (www.xing.com), which is an internet portal for professional business networking. Study participation was voluntary and anonymous, and participants were told that the purpose of the study was to compare different forms of methods to calculate the utility of an HRM intervention.

Out of 660 potential participants, 241 (36.5%) responded. To reduce the potentially negative impact of dropout in internet-based research (Bosnjak, 2001), we included a seriousness check (Reips, 2002). In other words, we asked participants at the beginning of our questionnaire if they seriously wished to participate in this study. Only data from participants who indicated their seriousness were analyzed. Participants who indicated that they only wanted to look at the online questionnaire were removed from further analysis. Thus, the sample size was 151 (22.9%) managers.

To ensure that respondents were key informants (Chen, Farh, & Macmillan, 1993; Kumar, Stern, & Anderson, 1993), we measured their involvement in human resource-related decisions. Respondents were therefore asked to state how many employees they supervise. On average, participants led a group of 22 people (*SD* = 29.4). However, seven respondents did not supervise any employees. In line with key informant methodology (Kumar et al., 1993), these seven respondents were excluded.

The final sample of 144 (21.8%) managers comprised 81.6% males and 18.4% females. Several participants had completed only the compulsory nine years of public schooling (1.4%). A fifth of the participants (20.6%) had been to a vocational training school, completing another three to four years of apprenticeship. Most of the participants had a Bachelor's degree, had attended universities of applied sciences, or had comparable further

education (42.6%). A quarter of the participants had a university degree equivalent to a Master's (25.5%). A tenth held a PhD or Master of Business Administration (9.9%). The average duration of experience working in the current function was 9.8 years (*SD* = 7.6).

Procedure & Stimulus Material

Two scenarios of utility analysis in the personnel training context served as independent variables. Each participant was randomly assigned to one of these two scenarios.

Both scenarios began with the same short introduction, describing that the manager was to assume to role of Vice President of a large company in the financial services sector (following Macan & Foster, 2004). The introduction also contained information about this company and the job of the employees, information pertaining to declining performance of employees currently holding this job, a description of the current training course and its goals, and the qualifications of the consultant presenting the utility analysis of this training program (following Macan & Foster, 2004). In order to stay close to the managers' information perception habits, we presented the stimulus material in a slide-show-like manner, as slideshows are commonly used to present information to managers, especially in the HRM context (Wempen, 2007).

Both slideshows presented participants with the following information: an explanation of the method used to calculate the monetary value (i.e., single-attribute utility analysis or causal chain analysis), information about the efficiency of the training method and the procedures used to assess this efficiency, as well as the cost of the training course. On the final slide, both scenarios led to the same estimate of monetary return of investment.

The single-attribute utility analysis version stemmed from Mattson (2003), consisting of a single-attribute utility analysis model to estimate the monetary return of a training program. The utility formula is that suggested by Cascio and Boudreau (2008, i.e., Equation 2). The second version consisted of a causal chain analysis-based estimation of the same

program. We developed and tested this scenario together with trainers and training program managers from the in-house business school of a Swiss bank. To design the final model, we determined the parameters to be included, as well as their interlinkages, together with managers, trainers and training program managers, as recommended by several authors (Cascio, 2000; Rowold & Mönninghoff, 2005). To calculate this model, we used data that already existed in a bank, making further data collection unnecessary. Data of employees' organizational commitment stemmed from a bank-wide employee survey and was measured using a six-item short form of the organizational commitment questionnaire developed by Mowdy, Steers and Porter (1979). Customer satisfaction was obtained from the company's marketing department and had been collected through structured telephone interviews. Financial data were delivered to us by the bank's internal financial controlling department. It consisted of an index of financial key performance indicators (e.g., net new assets, mortgage volume net increase, and credit card sales). We calculated the unstandardized path coefficient and the relationship of the training program with customer satisfaction, employee commitment and financial gain. Based on the data from the bank, this scenario led to the same return on investment as the single-attribute utility analysis scenario.

To ensure that potential differences in the dependent variables were not caused by the effort required by participants to process the scenarios (Carson et al., 1997), we parallelized the two scenarios in terms of reading ease and execution time. Both scenarios used exactly the same introduction text (one slide) and five subsequent slides to outline one of the two different methodologies of utility analysis models and its results. Table 1 shows the most important indices of German reading level statistics in order to outline the comparability of the two scenarios regarding reading ease (http://www.benutzerfreun.de/itext/cgi-bin/itext.pl). The German Flesch Reading Ease index and Amdahl's German understandability index consider both the average sentence length and the average number of syllables per word, but

with different weighting factors. The Wiener Formula for specialized texts compares the ratio of words with three or more syllables with the average number of words per sentence, the ratio of words with more than six letters and the ratio of monosyllabic words. Finally, the Gunning-Fog index accounts for the average number of words per sentence and the ratio of words with three or more syllables. As Table 1 shows, the reading level statistics were fairly similar. Furthermore, the average time to complete the study was 8 minutes and 55 seconds (*SD* = 7 minutes and 21 seconds) for the causal chain analysis and 10 minutes and 17 seconds (*SD* = 5 minutes and 5 seconds) for utility analysis, a non-significant difference ($t(140) = 1.24$, $p = 0.22$, two-tailed). Thus, the effort to process the two scenarios was approximately the same.

Table 1

Reading Level Statistics for the Single-Attribute Utility Analysis and the Causal Chain Utility Analysis

Index for reading ease	Single-attribute utility analysis scenario	Causal chain analysis scenario
German Flesch Reading Ease*	41	38
Amdahl's German understandability index**	48	43
Wiener Formula for specialized texts*	11	11
Gunning-Fog Index*	18	18

Note. *Higher values indicate a text that is more difficult to read. **Higher values indicate a text that is easier to read.

Measures

Understandability. The two items on this scale were those used in previous studies on reactions to utility analysis (Carson et al., 1997; Hazer & Highhouse, 1997; Mattson, 2003; Whyte & Latham, 1997). The items were "How well did you understand this consultant's proposal?" and "To what extent was the proposal clearly presented?"

Information quality. We used the Winkler et al. (2009) information quality scale: "The information from this utility analysis is the precise information I need", "The information from this utility analysis is exactly what I need to make a decision", "The information from this utility analysis is sufficient to enable me to make my decision", and "I am satisfied with the accuracy of the information from this utility analysis".

Perceived usefulness. The items (Winkler et al., 2009) were: "Using this utility analysis improves the quality of my decision", "I find this utility analysis useful for my decision", "Using utility information enables me to make a decision more easily", and "Using this utility analysis makes it easier to do my job as a manager". Due to reliability considerations, we dropped an additional item used by Winkler et al. (2009).

Information satisfaction. We assessed overall satisfaction with the utility analysis method by using a one-item omnibus measure introduced by Winkler et al. (2009) for measuring the global satisfaction with human resource information ("How would you rate your satisfaction with the human resource information available?"). In the context of information systems, the empirical results obtained by Rai et al. (2002) and Baroudi and Orlikowski (1988) confirmed that a single-item measure of user satisfaction can be used to assess overall user information satisfaction. Furthermore, within the context of I-O psychology, single-item indicators of job satisfaction show strong convergent validity with job satisfaction scales, and are thus considered to be robust (Wanous & Hudy, 2001; Wanous, Reichers, & Hudy, 1997).

Intention to use. This scale is based on that of Hazer and Highhouse (1997), describing the users' intention to use the information presented: "As the Vice President, I will use the utility information in deciding whether or not to continue the program", "As the Vice President, I will use utility analysis in future evaluations of other Human Resource programs"; "As the Vice President, I will encourage the Human Resources Department to continue doing utility analysis", "As the Vice President, I recommend utility analysis to other organizations", and "As the Vice President, this presentation of utility analysis is very influential in my final decision".

Results

Table 2 presents the means, standard deviations, reliabilities, and correlations among the variables of this study. We first used the General Linear Model procedure of SPSS 15.0 to conduct a MANOVA with the utility analysis method as the independent variable and the five variables from the human resource information success model as the set of dependent variables. We found a significant multivariate main effect for the utility analysis method, $F(1,8) = 6.91$, $p < 0.001$, $\eta^2 = .20$, indicating that there was a significant difference between the two methods of utility analysis. As shown in Figure 3, managers perceived causal chain analysis as being significantly more understandable ($M = 4.20$, $SD = 0.58$) than single-attribute utility analysis ($M = 3.48$, $SD = 0.88$), $d = .95$, $t\,(142) = 5.73$, $p < .01$. Causal chain analysis was perceived significantly higher in terms of information quality ($M = 2.91$, $SD = 0.67$) than single-attribute utility analysis ($M = 2.66$, $SD = 0.71$), $d = .37$, $t\,(142) = 2.20$, $p < .05$. Managers rated the two methods as similar, with no statistically significant differences in terms of perceived usefulness ($M_{causal\ chain\ analysis} = 3.56$, $SD = 0.75$; $M_{single\text{-}attribute\ utility\ analysis} = 3.39$, $SD = 0.83$), $d = .22$, $t\,(142) = 1.34$, $p = .18$, with a trend towards higher values for causal

chain analysis. The causal chain analysis led to significantly higher user information satisfaction (M = 3.50, SD = 0.61) than single-attribute utility analysis (M = 3.16, SD = 0.62), d = .54, t (142) = 3.26, p < .01, and managers intended to use causal chain analysis significantly more readily (M = 3.50, SD = 0.80) than single-attribute utility analysis (M = 3.10, SD = 0.87), d = .48, t (141) = 2.89, p < .01. Taken together, these findings show that hypotheses 1a, 1b, 1d, and 1e were confirmed, whereas hypothesis 1c was only descriptively confirmed, as causal chain analysis was descriptively but not significantly higher rated in terms of perceived usefulness.

Table 2

Means, Standard Deviations, Internal Consistencies, and Correlations

Variable	*M*	*SD*	1	2	3	4	5	6
1. Understandability	3.87	0.84	*.89*					
2. Information quality	2.79	0.70	.41**	*.79*				
3. Perceived usefulness	3.48	0.79	.53**	.66**	*.88*			
4. Information satisfaction	3.33	0.63	.68**	.81**	.75**	-		
5. Intention to use	3.30	0.86	.59**	.64**	.76**	.77**	*.86*	
6. Causal chain analysis (=1), single-attribute utility analysis (=0)	0.51	0.50	.43**	.18*	.11	.26**	.24**	-

Note. Cronbach's alpha estimates of reliabilities are on the diagonal. N = 144, with the exception of intention to use (N = 143).

p < .05; ** p < .01.

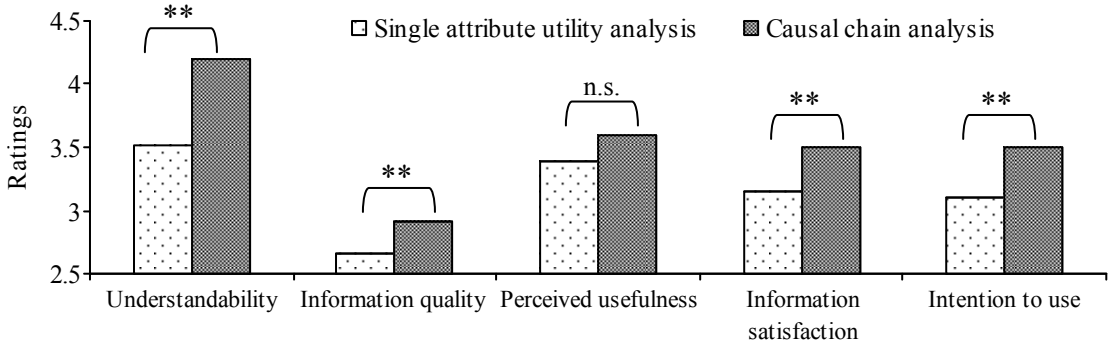

Figure 3. Means of variables related to human resource information success.

To test our mediation hypotheses, the approach suggested by Preacher and Hayes (2008) and Wood et al. (2008) was used. This parsimonious approach offers four important advantages compared to testing separate simple mediation models: (a) An overall mediation effect can be attributed to a set of variables, (b) it is possible to determine to what extent a set of variables mediate the effect between the independent and the dependent variable, (c) the likelihood of parameter bias due to omitted variables is reduced, conditional on the presence of other mediators in the model, and (d) this method allows the researcher to determine the relative magnitudes of the specific indirect effects associated with all mediators (see Preacher & Hayes, 2008, for a detailed discussion). We applied the SPSS macro provided by Preacher and Hayes (2008) to conduct this analysis. For all calculations, the independent variable (utility analysis method) was dummy-coded (single-attribute utility analysis = 0; causal chain analysis = 1), and *a paths* represented the paths between independent variable and mediator, *b paths* the paths between mediator and dependent variable, *c paths* the total effect of the independent variable on the dependent variable, *c' path* the direct effect of the independent variable on the dependent variable, and *ab paths* the indirect effects of the independent variables on the dependent variables through the proposed mediators. The most important indication of mediation is the difference between the significance level of the *c path* and the *c' path*, as well as the *ab path* (Sobel test).

The results, shown in Table 3, revealed that the *c' paths* became non-significant, while the *c paths* were all significant for both dependent variables, indicating a full mediation of the path between the utility method and both satisfaction with the information and intention to use by understandability and information quality. Additionally, the 95% confidence intervals of the bootstrap values of the Sobel test (bias corrected and accelerated 95% interval for total indirect effects with 5000 bootstrap resamples) lay outside zero for both information satisfaction (lower bound: .21; upper bound: .59) and intention to use (lower bound: .25; upper bound: .68). This indicates significant *ab paths,* and thereby confirms the previous indication of a mediation. Taken together, these findings support hypotheses 2b and 2c.

Table 3

Mediation of the Effect of Utility Analysis Method on Information Satisfaction and Intention to Use through Understandability and Information Quality

a paths	*t* values	*b paths*	*t* values	*c paths*	*t* values	*c' paths*	*t* values
Information satisfaction as dependent variable							
Method →		Understandability →		Method→		Method →	
Understandability	5.24**	Info. satisfaction	11.17**	Info. satisfaction	3.26**	Info. satisfaction	-.95 n.s.
Method →		Info. quality →					
Info. quality	2.20*	Info. satisfaction	15.04**				
Intention to use as dependent variable							
Method →		Understandability →		Method →		Method →	
Understandability	5.26**	Intention to use	5.26**	Intention to use	2.89**	Intention to use	-.24 n.s.
Method →		Info. quality →					
Info. quality	2.38*	Intention to use	2.38*				

Note: N =144, with the exception of intention to use (N = 143). *a paths* = independent variable → mediator. *b paths* = mediator → dependent variable. *c paths* = total effect of the independent variable → dependent variable. *c' path* = direct effect of the independent variable → dependent variable. The independent variable (utility analysis method) was dummy-coded (single-attribute utility analysis = 0, causal chain analysis = 1). Info. = information.

*p < .05; **p < .01

As a byproduct, the Preacher and Hayes' (2008) SPSS macro shows a contrast output to investigate whether there is a meaningful difference between understandability and information quality in terms of mediating power. In both mediation models, the contrast between understandability and information quality remained non-significant. This indicates that these two variables account similarly for the mediation effect.

Discussion

This study compared single-attribute utility analysis with causal chain analysis, and revealed that causal chain analysis is more readily accepted by managers than single-attribute utility analysis. For four of five variables related to human resource information success, we found higher values for causal chain analysis. The largest difference was understandability (d = .95), pointing to one of the key strengths of causal chain analysis. Understandability and information quality simultaneously and fully mediated the effect of a given utility analysis method on user satisfaction and the intention to use.

The higher acceptance of causal chain analysis fits in nicely with the finding of Hazer and Highhouse (1997), who found that the CREPID methodology of determining SD_y yielded the least favorable evaluation of managers and explained this with the argument that the CREPID methodology is particularly difficult to explain and understand (Highhouse, 1996). The same explanation seems to come into play when causal chain analysis and single-attribute utility analysis are compared: Because causal chain analysis is less difficult to understand, it is preferred by managers.

Several authors (Bobko, Karren, & Kerkar, 1987; Burke & Pearlman, 1988; Carson et al., 1997; Macan & Highhouse, 1994; Rauschenberger & Schmidt, 1987) have speculated that managers' acceptance of a given utility analysis is less a function of the content of the utility information and more due to the manner of its presentation. They argued that the challenge for researchers does not lie in addressing technical issues of utility estimation so much as in

ways of communicating utility estimates to organizational decision makers. Thus, the superiority of causal chain analysis may be due to its graphical representation as a path model compared to the presentation as a mathematical formula within single-attribute utility analysis. Nevertheless, positive reactions to utility information cannot solely be attributed to the way in which it is presented: Lemming and Macan (2009) showed that including visual information in their scenarios did not significantly improve respondents' reactions. Their results may also point to HRM professionals' reluctance to deal with mathematical formulae, possibly due to a lack of experience (but see Mattson, 2003). This may explain the more positive results of causal chain analysis, as mathematical expressions are dispensable (however, mathematical expressions are of course used to calculate path models, but they are not shown and are replaced by arrows representing paths).

The second mediator, information quality, points towards another difference between utility analysis and causal chain analysis, which is that it incorporates intervening variables such as customer satisfaction and employee attitudes. This seems to be an explanation of what influences managers' evaluation in favor of causal chain analysis, as the process leading to a final monetary estimate becomes more transparent, granular, and potentially closer to managers' cognitive processes. Furthermore, in terms of information quality, the reason for the higher success ratings of causal chain analysis might be that the final monetary estimate of return is enriched with information about further important variables of business performance. This allows a more detailed justification of a potentially high return of an HRM initiative, inspires further discussion of the strategic goals of this specific HRM initiative, allows simulations of "what-if" scenarios, and finally gives a more complete picture of how an HRM intervention actually influences the mediating and the target variables.

To sum up, our results show encouraging evidence for managers' readiness to accept causal chain analysis, rather than single-attribute utility analysis. Acceptance may not be

equivalent to success, but the acceptance of a utility analysis method is an important precondition for success (Petter, DeLone, & McLean, 2008).

Limitations

The measures used in this study were gathered from a single questionnaire, and each participant completed the questionnaire at one point in time. This introduces two potential drawbacks to this study: First, satisfaction and intention to use were measured at the same time as their mediators (i.e., understandability and information quality). This may limit the justification of causal inference (James & Brett, 1984; Wood et al., 2008). However, as the evaluation of a utility analysis method typically occurs within a very short time span (e.g., during a utility analysis presentation of an internal or external consultant), we expect this drawback to be negligible.

A second possible problem is common method bias. To address this issue, we used Harman's one-factor test by including all items from all of the constructs in the study into a confirmatory factor analysis in order to determine whether the majority of the variance can be accounted for by one general factor (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). This resulted in a very low model fit (RMSEA = .151; CFI = .822, NNFI =. 767, IFI = .825), indicating that common method variance may not be a problem in this study. This is in line with arguments claiming that concerns about common method variance are likely to be overstated (Spector, 2006).

Future Research

One of the basic assumptions of causal chain analysis is that it implies a causal connection between HRM interventions and variables such as employee commitment, customer satisfaction or financial company performance. These paths have been challenged (e.g., Wright, Gardner, Moynihan, & Allen, 2005), and research has been less than conclusive

when it comes to other causal connections that are a vital part of any causal chain analysis (Cascio & Boudreau, 2008; Ryan, Schmit, & Johnson, 1996; Schneider, Hanges, Smith, & Salvaggio, 2003). Even though there is encouraging evidence for many of these possible links (e.g., Harrison, Newman, & Roth, 2006), certainty can only be gained by conducting further longitudinal studies like the encouraging study by Birdi et al. (2008). Second, a further direction for future research relates to the appropriate time lag that should be assumed within a causal chain analysis model, as there is no consensus in the academic literature about what the most appropriate time lag would be (Cascio & Boudreau, 2008). On the contrary, recent studies show that the strength of the connection can heavily depend on the chosen interval for measurement (Riketta, 2008; Schneider et al., 2003). A third research direction points towards the level of aggregation, with results suggesting that relationships might be more powerful and stable at the business-unit or work-group level of analysis rather than the individual level (Cascio & Boudreau, 2008; Riketta, 2008; Schneider et al., 2003).

Practical Implications

In terms of practical implications, our results emphasize the importance of providing understandable information that is close to the users' requirements and quality needs. If these basic conditions are satisfied, then a given utility analysis is likely to be accepted by HRM decision makers. In our study, causal chain analysis proved to fulfill these criteria to a much greater extent than single-attribute utility analysis.

For practitioners, causal chain analysis offers a powerful alternative to the standard approach of utility analysis, particularly as our results showed significantly higher values for managers' intent to use this method, and we hope that many organizations will experience the potential of causal chain analysis in the future. Nevertheless, a number of challenges arise: Data collection and annual updates may be time-consuming and expensive, statistical knowledge is required to perform the statistical analysis, and the available data have to fulfill

many criteria (e.g., completeness of the data set, reliability, validity, stability of the units of investigation over time, continuous use of measurement procedures). Even though such hindrances might seem daunting at first glance, the potential gain of a tool that can effectively influence managers' decisions regarding a favorable evaluation of HRM investments is likely to pay off. Indeed, for many organizations, the barrier that needs to be overcome might be lower than expected, as Lawler (2004) found that eighty percent of organizations have an enterprise-wide HRM information system that could be linked to business data. Therefore, the potential of causal chain analysis appears to be huge, as the use of metrics and analytical procedures such as causal chain analysis to connect HRM investments to business outcomes is within reach once the right data are available.

Conclusion

Utility analysis research nowadays finds itself in a paradoxical trap: Although HRM departments are becoming increasingly interested in demonstrating the contribution of HRM to the success of organizations, the standard answer of industrial and organizational psychology – single-attribute utility analysis – seems to be futile (Latham & Whyte, 1994). The powerful causal chain form of utility analysis might provide a way out of this trap, helping HRM to position itself as a truly strategic partner supporting vital decisions about human capital (Cascio & Aguinis, 2008).

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Chapter 3

Causal Ordering of Job Attitudes and Performance at the Business-Unit Level

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Abstract

Job attitudes and performance are correlated, but which causes which? Despite a long-lasting debate and extensive research about this question, the potential causal ordering of the employee attitude – job performance relation is still not clear. Based on expectancy-based theories of motivation and adaptation-level theory, we develop arguments on why the influence of performance on subsequent attitudes might be less persistent over time than vice-versa. We contrasted both causal directions within a data set of business-units of the retail banking division of a large Swiss bank for the period of 2005-2008, allowing for a controlled environment and consistent data capturing over time. We compared the relationship of aggregated job attitudes (organizational commitment and job satisfaction) with two performance indicators (financial achievement and customer satisfaction). Results indicated that employee attitudes had a more persistent influence on performance at the business unit level than vice-versa. This suggests that employee attitudes may come first and that practitioners who aim to boost performance by increasing employee attitudes might be well advised to do so.

Introduction

The study of the relationship between job attitudes and job performance is one of the most established research traditions in industrial-organizational psychology (Harrison, Newman, & Roth, 2006; Judge, Thoresen, Bono, & Patton, 2001; Riketta, 2008). While several meta-analyses (e.g., Cooper-Hakim & Viswesvaran, 2005; Harrison et al., 2006; Harter, Schmidt, & Hayes, 2002; Judge et al., 2001; Meyer, Stanley, Herscovitch, & Topolnytsky, 2002; Riketta, 2002) have shown that positive job attitudes, such as commitment and satisfaction, are related to performance, the debate about the likely causal relationship between job attitudes and performance is far from being resolved (e.g., Harrison et al., 2006; Judge et al., 2001; March & Sutton, 1997; Riketta, 2008; Schneider, Hanges, Smith, & Salvaggio, 2003). Thus, although many organizations invest large amounts of money into employee attitude surveys and use the results to develop actions pointed towards increased employee commitment, it is still just a hope that this leads to superior firm performance (e.g., Schneider et al., 2003; Wright, Gardner, Moynihan, & Allen, 2005).

The vast majority of studies cannot address timing issues because of their cross-sectional designs. The central aim of the current study, therefore, is to shed light on some of the key questions surrounding linkage research by using longitudinal data: Do job attitudes influence performance, or is it the other way around? Are job attitudes and performance equally persistent in influencing each other? We develop theoretical arguments supporting why the influence of attitudes on performance should be more persistent over time than the influence of performance on attitudes. To test this, our research compares 1-year, 2-year, and 3-year lags of employee attitudes (job satisfaction and organizational commitment) with two performance criteria (financial performance and customer satisfaction) at the business-unit level of analysis. This study is the first to examine likely causal relations and timing issues

within a four-wave data set at the business-unit level, including both financial performance and customer satisfaction.

Before we describe the theoretical background of this study, we first explain the advantages and the importance of focusing on the business-unit level of analysis and of conducting multi-wave studies, and we define our variables.

Business-Unit-Level of Analysis

An appropriate level of analysis for the investigation of potential causal ordering of job attitudes and performance should be what is called the "decision-making unit" in operations research (Gelade & Ivery, 2003). In most organizations, performance is determined not only by the efficiency and productivity of individuals, but from higher-level organizational entities such as business-units, departments, or teams. Examples of such decision-making units are the branches of a bank, plants of a factory, or stores in a retail chain. Such units can be compared with each other if they use the same kind of resources and generate the same kind of outputs. Studying data at the business-unit level is important because this is the level at which employee survey data are typically reported (Gelade & Ivery, 2003; Harter et al., 2002). Business-unit-level research provides opportunities to establish linkages to outcomes that are directly relevant to the business, and many types of organizational performance indicators exist often only at the group level (e.g., customer satisfaction, profitability, and productivity; Rogg, Schmidt, Shull, & Schmitt, 2001).

Additionally, the aggregation of individual level data has some methodological advantages: It leads to a more reliable measurement of data collected at the individual-level due to a reduction in error variance (LeBreton & Senter, 2008), and single-item scores at the business-unit level are similar in reliability to subscale or dimension scores at the individual level of analysis because each business-unit item score is an average across many different

individual-level scores (Harter et al., 2002). Additionally, the collection of both attitudinal and performance related data within the business-units of one single organization ensures a high level of standardization of the measured variables and controls for the influence of organizational specific conditions and policies.

Multi-Wave Data Capturing

Some authors have argued that the most convincing causal evidence comes not from one single study but from a multitude of types of evidence and studies of change over time (e.g., Harter et al., 2002). Therefore, we suggest looking at multiple combinations of correlates over time to find out if they result in a consistent pattern. In the case of investigating potential causal ordering, this requires more than two waves of data. Furthermore, it is best to conduct a multi-wave design with equal time lags (Zapf, Dormann, & Frese, 1996), because a meta-analytic procedure (pooling correlational data over multiple instances of the same time lags) can be applied, which allows researchers to strengthen the statistical inference (Hayes, 1998) and to simplify the presentation of complex relationships (c.f., Schneider et al., 2003).

Job Attitude and Performance Variables

We use the term job attitude as the evaluation or personal importance of job-related targets (e.g., organization, work group, job as a whole). Probably the two most frequently investigated job attitudes are organizational commitment and job satisfaction (Harrison et al., 2006; Riketta, 2008). Organizational commitment is defined as “the relative strength of an individual’s identification with and involvement in a particular organization” (Mowday, Steers, & Porter, 1979, p. 226) and as “willingness to persist in a course of action” (Cooper-Hakim & Viswesvaran, 2005, p. 241). Job satisfaction refers to an emotional state that results

from the evaluation or appraisal of one's job experiences (Locke, 1976) or to a psychological state that is equally represented by cognitive and affective indicators (Brief & Weiss, 2002). Despite conceptual and empirical distinctions (e.g. Tett & Meyer, 1993), job satisfaction and organizational commitment have some theoretical and empirical commonalities (Harrison et al., 2006). In particular, LePine et al. (2002) showed a meta-analytic correlation between commitment and job satisfaction of $\rho = .60$.

In linkage research, a common variable used to capture business performance is financial performance (e.g., Schneider et al., 2003). However, performance is not restricted to the financial dimension only and other studies include variables such as customer satisfaction (e.g., Harter et al., 2002). Customer satisfaction is an important driver of firm profitability and is a central construct in marketing research (Luo & Homburg, 2007). A meta-analysis of relationships linking employee job satisfaction to customer satisfaction shows that, cross-sectionally, the two are positively related, yielding an attenuation-corrected mean correlation of $\rho = .25$ (Brown & Lam, 2008). Even though measurement instruments of customer satisfaction typically vary from company to company (Harter et al., 2002), they usually refer to customers' loyalty and their willingness to refer and recommend to others (e.g., friends, family, colleagues) to do business with the respective company (Verhoef, Franses, & Hoekstra, 2002). It is generally accepted that customer satisfaction drives customer behavior patterns that result in positive business outcomes (e.g., Keiningham, Perkins, & Evans, 2003).

Theoretical Models

Various models exist that aim to explain positive correlations between job attitudes and performance (e.g. Brief & Weiss, 2002; Brown & Peterson, 1993; Harrison et al., 2006; Judge et al., 2001; Meyer & Allen, 1997; Mowday, Porter, & Steers, 1982; Staw, Sutton, & Pelled, 1994). We summarize the most prominent models in the following section.

Model 1: Job attitudes cause performance. This model suggests a causal effect of attitudes on job performance. Probably the oldest explanation for why attitudes cause performance is that attitude objects cause behavior that is in line with a favorable evaluation (Eagly & Chaiken, 1993). This view is often attributed to the human relations movement (Judge et al., 2001; Strauss, 1968). Model 1 states that attitudes function as facilitators and guidelines of behavior (e.g., Judge et al., 2001) and it refers to the energizing and facilitative effects of positive affect as one component of satisfaction at the workplace (e.g., Staw et al., 1994). Furthermore, it points to the motivational effects of the personal importance or identification with the job or organization, for example as a component or consequence of commitment (Meyer, Becker, & Vandenberghe, 2004). For customer satisfaction, the same argument can be found in the marketing literature: It suggests that better employee attitudes and commitment determine customer service quality and, through improved service quality, drive customer satisfaction (e.g., Hartline & Ferrell, 1996; Heskett, Jones, Loveman, Sasser, & Schlesinger, 1994; Homburg, Wieseke, & Hoyer, 2009; Schlesinger & Zornitsky, 1991; Tornow & Wiley, 1991). Even though model 1 represents the prominent theme in the literature (Judge et al., 2001), only a few studies have specified a unidirectional causal effect of job satisfaction on job performance, and findings from these studies are inconclusive (Judge et al., 2001).

Model 2: Performance causes job attitudes. In contrast to model 1, expectancy-based theories of motivation state that job attitudes follow from internal or external rewards (e.g., pay raise, bonus, recognition, feeling good at work) produced by performance (e.g., Lawler & Porter, 1967; Naylor, Pritchard, & Ilgen, 1980; Vroom, 1964). Schneider et al. (2003) suggested that performance yields positive aggregated employee attitudes as a consequence of rewards and the results of their multi-wave study in different companies partly supported this view. Similarly, in terms of customer satisfaction, Luo and Homburg (2007) argued that

satisfied and loyal customers lead to a more positive atmosphere in companies and therefore to an increase in job satisfaction because employees enjoy their jobs more. Another explanation in favor of model 2 is that people adjust their attitudes to their behavior, in order to achieve cognitive consistency and to rationalize their actions as assumed by psychological theories of cognitive dissonance and of self-perception (Bem, 1972; Festinger, 1957; Staw et al., 1994). Model 2 has received some empirical support (Brown, Cron, & Leigh, 1993; Darden, Hampton, & Howell, 1989; Schneider et al., 2003; Stumpf & Hartman, 1984). Following the logic of model 2, job attitudes would be related to preceding business-unit financial performance and customer satisfaction.

Model 3: Performance and job attitudes cause each other. Combining these two viewpoints leads to reciprocal relationships, that is mutual causal effects between job attitudes and job performance (e.g., Sheridan & Slocum, 1975; Wanous, 1974). Reciprocal models have no distinct theoretical foundation and rather are hybrid models of the previous two approaches (Judge et al., 2001), leading to a bidirectional connection between indicators of job attitudes and performance. Sheridan and Slocum (1975) and Wanous (1974) provided some empirical evidence for model 3. Based on all three models we hypothesize:

Hypothesis 1 a): There will be a positive cross-sectional correlation between organizational commitment and business-unit financial performance.

Hypothesis 1 b): There will be a positive cross-sectional correlation between organizational commitment and customer satisfaction.

Hypothesis 1 c): There will be a positive cross-sectional correlation between job satisfaction and business-unit financial performance.

Hypothesis 1 d): There will be a positive cross-sectional correlation between job satisfaction and customer satisfaction.

The role of time

Expectancy-based theories of motivation (e.g., Naylor et al., 1980; Vroom, 1964) can be used as the basis of the argument that the effect of performance on job satisfaction might be a rather short-term phenomenon. Such theories state that job related attitudes such as job satisfaction follow from internal and external rewards. In an organizational context, typical examples for such rewards would be the recognition that comes out of a year-end performance appraisal, a pay-raise, or a bonus. Although this theoretical approach does not describe an explicit timeline outlining within what range of time these effects might occur, it can be extended by the hedonic treadmill model (Brickman & Campbell, 1971), a theory based on Helson's (1964) adaptation-level theory. This model helps to specify a time-line because it suggests that good and bad events only temporarily affect attitudes (Diener, Lucas, & Scollon, 2006). It suggests that the motivating effect of such rewards might be a short-term phenomenon only, because people adapt to improved circumstances to the point of affective neutrality, and in the long-run, rewards yield no real motivating effect (Kahneman, 1999). Adaptation herewith refers to a reduction in the affective intensity of favorable (and unfavorable) events over time and is supposed to be a function of past stimuli (Frederick & Loewenstein, 1999).

Although the hedonic treadmill model does not specify the range of time in which the adaptation effect might occur (i.e., what short-term and long-term effects are), such a specification can be made with the endowment/contrast model (Cheng, 2004; Tversky & Griffin, 1991). This model states that any pleasant stimulus reduces the pleasure associated with subsequent stimuli of the same kind (i.e., internal and external rewards). In an organizational setting, the motivational effect of rewards may diminish after one year, because after one year, new relevant stimuli are available (e.g., a higher or lower bonus for

the next year) based on the organization's systems time cycle (Mitchell & James, 2001), which usually is the economic year.

This viewpoint is supported by a variety of empirical evidence. Clark (1999) presents evidence from British data that job satisfaction is strongly related to changes (not absolute levels) in a worker's pay. Inglehart and Rabier (1986) show that life satisfaction and happiness scores are unrelated to the absolute level of current income, but are positively correlated with a measure of change in financial position over the past 12 months. Hamermesh (2001) found that changes in income produced only short-term changes in job satisfaction. Data on windfall income indicates that greater wealth can produce higher subjective well-being predominantly in the short-run (Diener & Biswas-Diener, 2002; Gardner & Oswald, 2001). Gardner and Oswald (2007) found that one year after a lottery win, the level of psychological strain and happiness is similar to one year before the lottery win. Suh, Diener, and Fujita (1996) found that good life events (e.g., promotion, raise, improvement in financial status) affected happiness only if they occurred in the past three months. Evidence from literature on the impact of salary increase on attitudes showed that salary increases only lead to short-term improvements due to adapted aspiration (Ahuvia, 2008; Easterlin, 2001; Frey & Stutzer, 2000, 2002). A study by Riketta (2008) also supports this view, as he found that the effect of job attitudes (i.e., job satisfaction and commitment) on performance persisted over several intervals (with stronger effects for shorter than for longer time lags), while the effect of performance on job satisfaction was non-significant for short time-lags and significantly negative for moderate time lags. The Schneider et al. (2003) study showed that the effect of earnings per share (i.e., performance) on satisfaction with pay (i.e., attitudes) diminishes over a four-year period, while satisfaction with pay emerged as a significant predictor of performance over the same period, which also supports this line of argumentation. Therefore, we expect that benefits influence job attitudes on a rather short

term (no longer than one year) perspective, and the possible consequences of good performance (e.g., pay raise, bonus) are unlikely to influence attitudes over a period of more than one year.

In contrast, we expect the influence of job related attitudes to be more persistent, because they can be expected to be relatively stable over time (e.g., Dormann & Zapf, 2001; Lam, 1998). For example, job satisfaction and organizational commitment showed significant stability over five years (Bowling, Beehr, & Lepisto, 2006), partly because they are strongly related to personality traits (Tziner, Waismal-Manor, Vardi, & Brodman, 2008) and they are hereditary (e.g., Frederick & Loewenstein, 1999; Haidt, 2006). Furthermore, several meta-analyses (e.g., Cooper-Hakim & Viswesvaran, 2005; Harrison et al., 2006; Harter et al., 2002; Judge et al., 2001; Meyer et al., 2002; Riketta, 2002) have shown that job attitudes are related to performance, with many of them assuming that job related attitudes are highly relevant to workplace behavior. As an example, a satisfied and committed sales representative of a financial service provider who has acquired a new customer at time t_1 is likely to generate profits (e.g., out of product sales and new monetary assets as important indicators of a financial service provider's financial performance) not just on a short term (i.e., 1-year lags) but also on a long term perspective (i.e., 2-year and 3-year lags), due to the customer's repurchase behavior.

We expect the same to be true for customer satisfaction as a performance indicator, because creating and maintaining customer loyalty in organizations is affected by employees' commitment (Singh, 2000). Building and maintaining long-term customer relationships is important to improve business performance, particularly for services such as banks (Ennew & Binks, 1996). If a customer has a positive experience with an employee, his repurchasing intentions, and thus company profits, are likely to increase (Walsh, Evanschitzky, & Wunderlich, 2008). As such, we hypothesize:

Hypothesis 2a): Employee commitment will predict financial performance not only in short-term (1-year lags) but also in medium term (2-year lags) to long-term (3-year lags).
Hypothesis 2b): Employee commitment will predict customer satisfaction not only in short-term (1-year lags) but also in medium term (2-year lags) to long-term (3-year lags).
Hypothesis 2c): Job satisfaction will predict financial performance not only in short-term (1-year lags) but also in medium term (2-year lags) to long-term (3-year lags).
Hypothesis 2d): Job satisfaction will predict customer satisfaction not only in short-term (1-year lags) but also in medium term (2-year lags) to long-term (3-year lags).

Hypothesis 3a): Financial performance will predict employees' commitment on a short-term (1-year lags) basis, but not in a medium (2-year lags) to long-term (3-year lags) basis.
Hypothesis 3b): Financial performance will predict employees' job satisfaction on a short-term (1-year lags) basis, but not in a medium (2-year lags) to long-term (3-year lags) basis.
Hypothesis 3c): Customer satisfaction will predict employees' commitment on a short-term (1-year lags) basis, but not in a medium (2-year lags) to long-term (3-year lags) basis.
Hypothesis 3d): Customer satisfaction will predict employees' job satisfaction on a short-term (1-year lags) basis, but not in a medium (2-year lags) to long-term (3-year lags) basis.

Thus, this study contributes to the literature on linkage research in several ways. First, we examine the effect of job attitudes on performance at the business-unit level within a four-year dataset, allowing for a stable setting and consistent data capturing. Previous studies on business-unit level data primarily focused on cross-level and two-year data sets (e.g, Gelade & Ivery, 2003; Gelade & Young, 2005; Harter et al., 2002; Koys, 2001). Second, we include customer satisfaction as a performance indicator, which has not been studied over four years

in a multi-wave setting, despite sound arguments for both the theoretical and the practical importance of this variable over time. Third, we use theoretical arguments to explain timing differences on the effect of job attitudes on business unit performance and vice versa.

Method

Sample

We collected data from the business-units of the retail banking division of a large Swiss bank for the years 2005-2008. The average sample size per business-unit was 18 people (*SD* = 9). The number of data-points from the different business-units varied from 42 (2007) to 34 (2005 and 2008) due to minor reorganizations (foundation of new or closing of old branch offices) and due to the availability of data (which was only granted when a business-unit contained more than 8 employees due to anonymity reasons).

Measures

Data for organizational commitment and overall job satisfaction stem from a yearly company-wide employee survey, conducted by an external service provider on behalf of the bank. The average response rate was 84% (*SD* = 11%). The surveys were administered between July and August every year and items were consistently used in the same format (6-point Likert scale). Participants were invited by email to fill in the surveys in an online form. Participation was encouraged but not mandatory and the participation was anonymous.

Organizational commitment. The items that were used to capture employees' organizational commitment stemmed from a 6-item short form of the organizational commitment questionnaire by Mowday et al. (1979). The original number of items was shortened to prevent survey fatigue (Stanton, Sinar, Balzer, & Smith, 2002). The items

referred to the employees' willingness to stay with the company, their willingness to go beyond what is normally expected, and how they talk to other people about how it is to work for this company. Due to copyright regulations of this external service provider, the exact items cannot be provided. A very similar item from the organizational commitment questionnaire (Mowday et al., 1979) is "It would take a lot to get me to leave this company." Other banks rely on a very similar approach to measure employee commitment (e.g., Fischer & Mittorp, 2002).

Job satisfaction. Employees' overall job satisfaction was measured by the item "I truly enjoy my day-to-day work tasks." Within the context of industrial-organizational psychology, global single-item indicators of job satisfaction show strong convergent validity with job satisfaction scales and are considered to be more robust than the scale measures of overall job satisfaction and therefore acceptable (Wanous & Hudy, 2001; Wanous, Reichers, & Hudy, 1997). Additionally, Brown and Lam's (2008) meta-analysis showed that studies using global job satisfaction measures yield higher correlations with indicators of customer satisfaction than multiple measures on job satisfaction facets, which indicates the usefulness of global single-item measures in the context of our study.

Financial performance index. A common measure used to cover business-unit financial performance in retail banking is a composite measure that contains the net new assets, the overall mortgage volume net increase, and the sales achievement (e.g., of structured products). The bank where this study's data stems from developed and refined such a measure over many years. It serves as the internal financial controlling and goal setting processes and is available at the business-unit level on a monthly basis. For our analysis, we used a twelve-month average measure (January to December). All values are weighted, depending on the size of the respective business-unit and represent an index for the financial performance of each business-unit. The components of this index show strong inter-

correlations. Nevertheless, we treat them as an index rather than a scale, because this measure may be better construed as outcomes that together form an index of accuracy rather than as manifestations of a single underlying construct (Edwards & Bagozzi, 2000; Streiner, 2003; Trougakos, Beal, Green, & Weiss, 2008).

Customer satisfaction. Data on customer satisfaction stems from yearly data collection efforts between March and August, where about 2000 customers are asked for their service quality perceptions during a structured telephone interview. A key concept to cover the aspect of customer satisfaction and future growth that is used by this bank is to measure the customers' intention to recommend the services of the bank to others, measured by a single item ("How likely is it that you will recommend the services of this bank to a friend or colleague?"). This is a common method of assessing customer satisfaction in the marketing sciences, especially in the banking context (e.g., Kamakura, Mittal, de Rosa, & Mazzon, 2002).

Aggregation

We explored evidence related to the aggregation of these data to the unit-level of analysis by examining several commonly used statistics for justifying aggregation, that is $r_{wg(J)}$ (James, Demaree, & Wolf, 1984) for the multi-item measure (organizational commitment) and r_{wg} for the single item measure (overall job satisfaction). r_{wg} defines agreement in terms of the proportional reduction in error variance, meaning that higher scores indicate greater reduction in error variance and, thus, higher levels of agreement (LeBreton & Senter, 2008). Values of $r_{wg(J)}$ of above .70 have been used as the traditional cut point indicating high interrater agreement (Lance, Butts, & Michels, 2006; LeBreton et al., 2003, LeBreton & Setner, 2008). The averages for employee attitudes were calculated for each business-unit for each year of the data base and then the results were averaged. The average

$r_{wg(J)}$ for employees' organizational commitment was .78, and the r_{wg} for overall job satisfaction was .83, indicating sufficient within-group agreement to aggregate both variables to the business-unit level of analysis.

Additionally, we calculated the intra-class correlation coefficient ICC(1), representing an assessment of the extent to which the mean rating assigned by a group of judges is reliable. Compared to the average ICC(1) value reported in organizational literature of .12 (James, 1982) and the values reported in earlier studies on employee attitudes and firm performance at the organizational level (e.g., Schneider et al., 2003, .05 - .19), our average value of .41 for organizational commitment and .31 for overall job satisfaction are very satisfactory. Unlike earlier studies, we omitted ICC(2) because this indicator is only appropriate when raters are nested in targets.

Table 1

Average Scale Intercorrelations between the Business-Unit Employee Attitude Scales and the Business-Unit Performance Indicators

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1.	Commitment 2005	(.89)														
2.	Commitment 2006	.30	(.89)													
3.	Commitment 2007	.40*	.44*	(.91)												
4.	Commitment 2008	.47*	.31	.61**	(.88)											
5.	Job satisfaction 2005	.65**	.15	.02	.17	-										
6.	Job satisfaction 2006	.16	.53**	.39*	.24	.19	-									
7.	Job satisfaction 2007	.45*	.33	.85**	.69**	.03	.31	-								
8.	Job satisfaction 2008	.28	.24	.44*	.64**	.34	.45**	.41*	-							
9.	Financial performance 2005	.47*	.47**	.23	.22	.22	.25	.33	-.07	-						
10.	Financial performance 2006	.55**	.56**	.37*	.14	.26	.41*	.32	.10	.78**	-					
11.	Financial performance 2007	.42*	.46**	.59**	.30	.17	.45**	.53**	.32	.63**	.69**	-				
12.	Financial performance 2008	.52**	.43*	.25	.54**	.42*	.45**	.33	.53**	.59**	.50**	.41*	-			
13.	Customer satisfaction 2005	.47*	.33	.04	-.03	.15	-.17	.03	-.23	.49**	.44**	.22	.10	-		
14.	Customer satisfaction 2006	.45*	.33	.30	.14	.14	-.03	.13	-.03	.53**	.56**	.34*	.29	.83**	-	
15.	Customer satisfaction 2007	.51**	.48**	.29	.25	.10	-.01	.25	.13	.48**	.49**	.40*	.34	.80**	.83**	-
16.	Customer satisfaction 2008	.29	.32	.16	-.03	-.01	-.08	.00	-.10	.30	.43*	.27	.09	.80**	.80**	.74**

Note. Scale intercorrelations were calculated at the business-unit level of analysis. Cronbach's alphas are on the diagonal. $N = 34$ to 42.

*$p < .05$; **$p < .01$.

Results

Strategy of Analyses

Because we had multi-wave data from employee attitude surveys, the financial business-unit performance indicators and the customer perceptions, the stability over time of these data sets were calculable and lagged analysis relating the data sets were feasible. Table 1 shows both the intercorrelations of the measures used in this study as well as the stabilities. We accept our set of hypotheses 1a to 1c (job attitudes and performance correlate cross-sectionally; average weighted correlations: commitment – financial performance, $r = .54$, $p < .00$; commitment – customer satisfaction, $r = .27$, $p < .05$; job satisfaction – financial performance, $r = .42$, $p < .05$). We reject hypothesis 1d (job satisfaction – customer satisfaction) due to a non-significant average weighted correlation of $r = .07$, $p > .05$. The ranges for the stability values are comparable to earlier studies in the context of employee attitudes and firm performance (e.g., Schneider et al., 2003). The statistics of interest are the cross lagged correlations for the one-, two-, and three-year time lags (Schneider et al., 2003). First, we analyzed every single time lag for the three years separately. Second, we calculated weighted averages, where each correlation for a given lag was weighted by the number of business-units involved in the calculation of that correlation for that lag, thereby equating correlations over time for the sample size on which they were based (here: the number of business-units). More specifically, before averaging the correlations for a particular time lag, we tested whether these correlations were from the same population (Schneider et al., 2003). We performed the test of homogeneity of correlations (Hedges & Olkin, 1985) to test whether the correlations from the same time lags could be averaged. None of the pooled correlations revealed significant Q values, indicating that homogeneity existed and therefore that pooling the correlations was acceptable.

Next, we examined the magnitude of the correlations of attitudes as predictor versus performance as predictor (see Table 2). Attitude as predictor consistently yielded higher correlations with proceeding performance than vice versa. More specifically, there was not a single case where performance as predictor yielded a higher correlation value than attitude as predictor. Most of the attitude –as predictor correlations reached statistical significance, which was not the case for the performance –as predictor correlations. This is the first indication that attitudes are a better predictor of proceeding performance than vice versa. Additionally, none of the 2- and 3-year lags of performance as predictor reached significance.

Table 2

Average r, Δr, and Confidence Intervals of Differences in Correlations for Attitudes as Predictor and Performance as Predictor

Time lags	Attitude as predictor	Average *r*	Performance as predictor	Average *r*	Δ*r*	CI delta 90%		CI delta 95%	
						LB	UB	LB	UB
1-year lags	Commitment	.42*	Financial performance	.38*	$.04^{n.s.}$	-.25	.32	-.30	.38
		.37*	Customer satisfaction	.29*	$.07^{n.s.}$	-.22	.37	-.28	.43
	Job satisfaction	.35*	Financial performance	.30*	$.05^{n.s.}$	-.27	.39	-.33	.48
		$.04^{n.s.}$	Customer satisfaction	$.03^{n.s.}$	$.01^{n.s.}$	-.33	.36	-.40	.43
2-year lags	Commitment	.42*	Financial performance	$.18^{n.s.}$	$.23^{\#}$	-.08	.54	-.13	.59
		.41*	Customer Satisfaction	$.09^{n.s.}$	$.33^{\#}$	-.01	.64	-.07	.69
	Job satisfaction	.32*	Financial performance	$.22^{n.s.}$	$.09^{n.s.}$	-.25	.43	-.32	.49
		$.01^{n.s.}$	Customer satisfaction	$.00^{n.s.}$	$.01^{n.s.}$	-.35	.37	-.41	.43
3-year lags	Commitment	.52**	Financial performance	$.22^{n.s.}$	.31*	.01	.60	-.05	.65
		.29*	Customer satisfaction	$-.03^{n.s.}$	$.32^{\#}$	-.02	.63	-.08	.68
	Job satisfaction	.42*	Financial performance	$-.07^{n.s.}$	.49*	.13	.81	.06	.86
		-.01	Customer satisfaction	$-.23^{n.s.}$	$.22^{n.s.}$	-.14	.54	-.20	.60

Note. Δ*r* = Difference between the two correlations, where the indicated significance level represents the results according to the procedure for comparing non-independent correlations suggested by Steiger (1980). CI = Confidence interval based on Zou (2007). LB = Lower bound. UB = Upper bound.

$^{\#}p < .10$; *$p < .05$; **$p < .01$.

As a next step, we compared the cross-lagged correlations of the three different time lags by applying the procedure suggested by Steiger (1980) for comparing non-independent correlations. This provides us with an indication of whether the differences in the lagged correlations (Δr) are statistically significant. The larger the Δr, the more likely there is a difference in predictive power of one predictor over the other, and this provides an indication of whether attitudes or performance is a better indicator of the respective criteria. The Δr values in the 1-year lags were all close to zero, indicating that no differences in the predictive power of attitudes and performance may exist in 1-year lags. As the first analytical step revealed meaningful correlations for both causal directions, this points towards a reciprocal relationship of the data (except for job satisfaction – customer satisfaction, where we found no significant correlation). This picture changes when looking at the 2-year lags: While the averaged correlations for attitude as predictor remained significant and high, the average *r*'s of performance as predictor drop, and the resulting Δr become significant at the $p < .10$ level for commitment as predictor of financial performance and customer satisfaction. Even though the significance level did not reach the conventional $p < .05$ level, the differences in predictive power ($\Delta r = .23$; $\Delta r = .33$) reach medium effect sizes (Cohen, 1992) and such values range in the middle to upper range of effects that can be found according to Hemphill's (2003) empirical guidelines for interpreting the magnitude of correlation coefficients. The 3-year lags showed even greater Δr values that became significant at the $p < .05$ level for commitment as predictor of subsequent financial business-unit performance and for job satisfaction as predictor of future financial performance.

In addition, we calculated confidence intervals. Critics argue that null-hypothesis significance testing is easily misunderstood (e.g., Hunter, 1997) and that this approach of inference tends to obscure study findings by encouraging attention to *p* values or even number of asterisks reported in tables, rather than the actual effect size (e.g. Hoyt, Imel, & Chan,

2008). These authors suggest evaluating the practical significance of the relations under investigation, rather than the statistical significance (Hoyt et al., 2008; Kirk, 2007). In the case of comparing correlations, a confidence interval can avoid some of the problems mentioned above by providing a range of plausible parameter values and thus may be more informative when reporting research work (Olkin & Finn, 1995). Zou (2007) has recently developed a general method for comparing correlation coefficients taking into account both the stabilities and the asymmetry of the confidence limits around individual effect sizes. He has shown that this method has statistical properties superior to available alternatives, especially for small sample sizes. We applied the SAS macro for nonoverlapping correlations described by Zou (2007) that he kindly provided to us, and those results are presented on the right-hand side of Table 2 (i.e., confidence intervals at the 90%-level and the 95%-level).

The confidence intervals revealed that the range covered a large area in the positive range, especially for the 2-year lags and the 3-year lags. As an example, the 95% confidence intervals for commitment as predictor of subsequent 2-year financial business-unit performance ranged between -.13 and .59. This means that with 95% confidence, the difference between the two lagged correlations fall between -.13 and .59. Although this difference did not reach statistical significance at the 5% level (because the confidence interval contains zero), the difference could be as high as .59, and null hypothesis significance testing would have missed such information. However, the sample size (N = 34) led to a wide confidence interval that included 0, so the null hypothesis of no difference cannot be rejected. As another example, the 90% confidence intervals for employees' job satisfaction as predictor of subsequent 3-year customer satisfaction ranged from –.20 to .60, suggesting that satisfaction may be more predictive than vice versa, although the difference in correlation did not reach the 5% significance level given the sample size.

To summarize, employee attitudes were persistent indicators of subsequent performance indicators, except job satisfaction for customer satisfaction, thus we can accept

hypothesis 2a to 2c, and we reject hypothesis 2d. Furthermore we can accept hypothesis 3a to 3d because performance indicators were significant predictors of job attitudes on a 1-year perspective, but not on a 2-year to 3-year perspective. Thus, our results suggest that on a 1-year perspective a reciprocal relationship may exist. In turn, for 2- and 3-year lags, employee attitudes may be stronger predictors of proceeding performance than the other way around.

Discussion

The present study adds to the growing linkage literature by investigating the relationship between aggregated employee attitudes and business-unit financial performance and customer satisfaction over time. Our results suggested that employee attitudes and financial performance and customer satisfaction are reciprocally related when looking at 1-year lags, with the exception of employee job satisfaction, which did not have a significant relationship with customer satisfaction (which is true for all time lags under investigation). More importantly, the picture changed when we looked at the two-year lags, because we found reasonably strong correlations between previous employee attitudes and consecutive financial performance and customer satisfaction, but *not* in the reversed direction. Thus, cross-lagged panel correlations suggested that aggregated employee attitudes predict financial performance and customer satisfaction in the long run, but not vice versa. These results are in line with previous evidence on the individual-level of analysis (Riketta, 2008) and the organizational-level of analysis (Schneider et al., 2003).

In our introduction, we outlined three theoretical models that describe the relationship between employee attitudes and performance outcomes (i.e., job attitudes cause performance, performance causes job attitudes, and a reciprocal relationship between the two). Our results speak for a model that involves all three models. That is, in a one-year perspective, our results point to a reciprocal relationship, which is a combination of the two models stating a unidirectional influence of attitudes on performance or vice versa. After that period, the

results predominantly support a model that states a unidirectional influence of job attitudes on business-unit performance. What this shows is (a) how important the inclusion of theoretical considerations are in understanding the results of longitudinal analysis, (b) that multi-wave data sets with more than two data sets have advantages when it comes to the investigation of likely causal ordering, and (c) how important it is to retrieve highly reliable and consistent data (e.g., by collecting data at the business-unit level of aggregation) to prevent an attenuation of the phenomenon under investigation due to an increasing amount of error variance in measurement over time.

The longitudinal effects of job attitudes on business-unit financial performance and customer satisfaction seem to be remarkably high. The correlations we found often were higher than one would expect based on meta-analytical cross-sectional findings: The mean true correlation between overall job satisfaction and job performance at the individual level was estimated to be $r = .30$ in the study of Judge et al. (2001), while many of our correlations exceeded this value. Presumably, this is due to the very rigorous measurement practice by the organization from which the data of this study stems. In particular, the composite measure of financial business-unit performance is a construct that was refined during many years prior to our study. If the same calculations are redone with only one of the composites of the index (e.g., net new assets) for financial performance, the values become comparable with the values found in the meta-analysis by Judge et al. (2001). Also, our ICC values were satisfactory, which indicates relatively low levels of measurement error within our data, which in turn is likely to increase the strength of the effects.

Our results may be encouraging for practitioners, because a logical consequence of our findings is that human resource investments for increasing employee attitudes, if effective, might lead to long-term improvements of both financial performance and customer satisfaction. However, human resource practitioners need to be aware that several studies have shown that there are natural limits to the amount by which employee attitudes can be

improved (Bowling et al., 2006; Frederick & Loewenstein, 1999; Haidt, 2006; Tziner et al., 2008). Wright and Gardner (2005) noted that in much of the research on strategic human resources management (Huselid, 1995) the implicit presumption is that high-performance work practices (such as employee involvement, pay for performance, or skill acquisition; see Lawler, Mohrman, & Ledford, 1998) actually do have a direct effect on employee attitudes, which in turn yields improved individual and organizational performance. Yet, empirical evidence is rare, in part due to a lack of rigorous designs to test the hypothesis that human resource practices actually result in an increase in employee attitudes and thereafter in higher organizational performance in a causal sense (Wright et al., 2005). However, an alternative to these human resource investments is the idea of applying personality questionnaires in personnel selection procedures, because work related attitudes are strongly related to personality (e.g., Tziner et al., 2008). Furthermore, meta-analytical findings have shown that personality predicts performance. Therefore, practitioners seeking to increase both employee attitudes and performance are well advised to use a personality measure during selection processes (Barrick, Mount, & Judge, 2001; Ones, Dilchert, Viswesvaran, & Judge, 2007).

Furthermore, our results can be relevant for practitioners when it comes to accounting the utility of human resource initiatives: Some authors have suggested basing such calculations on cause-effect relations based on unstandardized path coefficients (Boudreau & Ramstad, 2003, 2007; Cascio & Boudreau, 2008). This notion was already mentioned in the context of personal selection by both Burke and Pearlman (1988) and Schmidt (1993) who offered percentage improvement in productivity as a potentially valuable means of expressing utility. The outcomes of such analysis are path coefficients or regression weights that give an indication of what the expected outcome in a dependent variable will be, based on a given change in the independent variable (Cascio & Boudreau, 2008; Gelade & Ivery, 2003; Gelade & Young, 2005; Mirvis & Lawler, 1977, 1983). The potential of such cost-benefit comparisons of attitude-behavior relationships in practice could be enormous (Boudreau &

Ramstad, 2007; Cascio & Boudreau, 2008), but only makes sense if the causal flow goes from attitudes to performance. Our results indicate that the potential causal ordering might indeed be from job attitudes to performance, thus confirming the basic assumption of these initiatives.

Finally we want to emphasize the importance of communicating effect sizes such that practitioners can understand their practical significance (Kirk, 2007; McCartney & Rosenthal, 2000). A useful tool for this purpose is the binomial effect-size display (Rosenthal & Rubin, 1982). Translated into this display, the present finding of the relationship between job satisfaction and subsequent 3-year financial performance of $r = .42$ means that business-units with higher job satisfaction have a 145% higher likelihood of belonging to the half with higher performance than those units with lower job satisfaction. As this is a rather impressive number, practitioners would likely continue to be willing to invest in measures of employee attitudes. An alternative way of communicating effect-sizes is to compare the correlational results to findings from other disciplines that are generally known, accepted or illustrative. For example, the correlation between male consumption of Viagra and sexual performance has been calculated to be $r = .38$ (Goldstein et al., 1998) which is similar to the relationship between employee job satisfaction and subsequent 3-year financial performance.

Limitations and Future Research

Some limitations have to be mentioned. First, our study was conducted within one organization within one country, so one could question the generalizability of the results. However, the potential benefit from a single-company study like this is that it allows to control for a number of variables such as geographical distinctness (Wright et al., 2005) and job complexity. Furthermore, the relatively homogenous market-environment in Switzerland controls for the local markets that could impact profitability (e.g., markets with higher socioeconomic conditions result in those business-units having naturally higher profits) and

the consistent measurement of both the performance and the attitude measures was guaranteed.

Second, although the logic of cross lagged panel correlation technique is intuitively appealing, some researchers have argued against using it (e.g., Campbell & Kenny, 1999; Zapf et al., 1996). They argued that the difference between the cross-lagged correlations also depends on the stabilities of both variables (Zapf et al., 1996). More precisely, the potential influence of the stabilities is that a significant cross-sectional correlation between two variables A and B at time t_0 will by trend be more likely to remain significant for the proceeding cross-lagged correlation for the predicting variable with the lower stability. For our data set this could mean that the persistent correlation of employee attitudes and subsequent performance indicators may partly be explained by the higher stabilities in the performance variables. However, the statistical methods applied in this study account for the potential effect of stabilities by including those correlations into the formulas and procedures applied (Raghunathan, Rosenthal, & Rubin, 1996; Steiger, 1980; Zou, 2007).

We encourage future studies to continuously look for opportunities to gather longitudinal data with at least two-wave datasets and, whenever possible, various sources of data. Otherwise, inferences of likely causal priority are very difficult to make. With an average sample size of 34 business-units, our sample size is relatively small. We encourage future studies to gather larger data sets, which would not only lead to smaller confidence intervals of the effects described, but also to a likely shift from cross-lagged panel correlation technique to hierarchical linear modeling (Bryk & Raudenbush, 1992).

Future research could also include potential moderators and mediators into timely specification of linkages. Earlier, we mentioned some of these potential variables (i.e., self-esteem, job complexity). Further moderating variables might be reward contingency (Podsakoff & Williams, 1986), the level of analysis (Brown & Lam, 2008), or the length of the measurement interval and type of job attitudes (Riketta, 2008).

Conclusions

This study extends prior work on the relationship between employee attitudes and business outcomes by exploring issues of likely causal ordering. Results provide positive support for employee attitudes as persistent predictors of business-unit financial performance and customer satisfaction for time lags of one to three years, whereas the effect of performance on job-attitudes diminishes after one year.

Therefore, the results show that employees' job attitudes are an important driver of both business-unit financial performance and customer satisfaction. Nevertheless, carefully designed research is needed in the future to provide further conceptual clarification of the underlying mechanisms of these relationships, as a variety of potential moderators and mediators of the relationship between job attitudes and performance may exist.

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General Discussion

The aim of the present thesis was to get deeper insights into key questions surrounding the topic of human capital analytics. First, we were interested in success factors of human capital information. Second, based on insights from the first study, we compared two sources of human resource information along these criteria. Third, we explored a precondition that is vital for many different forms of human resource information, including one of the sources described in study 2.

In what follows, I will first summarize the most important findings and conclusions from the three studies. After that, I will critically reflect on particular strengths and limitations. Finally, I will end with major implications for research and practice, which can be derived from the findings of this thesis.

Overview of the Main Results and Main Conclusions

Chapter 1 presents the results from an online survey we conducted to answer the question of what makes human resource information successful. The study supported a theoretical model from the information systems literature called Technology Acceptance Model (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989) in the human resource management context. The model consists of the following five key variables: ease of use, information quality, perceived usefulness, user information satisfaction, and information use. It is able to explain which variables are important for users of human resource information and how these variables are interlinked.

The results revealed that the Technology Acceptance Model can be applied in the human resource context, but with some modifications. In particular, we found a significant impact of ease of use and information quality on attitudes towards human resource information (i.e.,

perceived usefulness and user satisfaction). Interestingly, ease of use and user satisfaction do not directly influence human resource information use. Yet, the findings also revealed that managers used HRI on average between once a month and once every six months and that HRI use was primarily influenced by information quality and perceived usefulness.

Our study was the first to outline a theory-based model of the success factors of human resource information. We extended previous research in the field of human resource management by (a) selecting an adequate theory to explain human resource information success, (b) combining the results from earlier studies in the HR field with additional relevant variables from the IS success literature, and (c) testing this new model as a whole with a structural equation model.

The study presented in *Chapter 2* aimed to investigate the success factors of two methods of human capital analytics. More specifically, we were interested in potential advantages of an alternative method of utility analysis (i.e., causal-chain analysis) compared to an established method, that is single attribute utility analysis. Therefore, we compared both methods along the identified criteria of human resource information success from our first study.

The findings revealed that causal-chain analysis is more readily accepted by managers than single attribute utility analysis: For four of five variables related to human resource information success, we found significantly higher values for causal-chain analysis. The exception was perceived usefulness, where we found higher values for causal chain analysis, but the difference remained non-significant. The largest difference was understandability, which points to one of the key strengths of causal-chain analysis. Based on a mediation analysis, the study also provided an explanation of why these effects occurred: The effect of a given utility analysis method on intention to use and information satisfaction is simultaneously mediated by understandability and information quality.

Overall, the findings imply that causal-chain analysis is a powerful alternative of communicating the utility of HRM interventions. Our study was the first to show empirical evidence for the superiority of causal-chain analysis compared to single attribute utility analysis, which is still the most established form of utility analysis (Choragwicka & Janta, 2008).

Finally, the third study presented in *Chapter 3* referred to a basic assumption incorporated in the causal-chain analysis method of utility analysis from study 2, which is the implicit assumption that improved employee attitudes might lead to improved performance. Therefore, we contrasted both causal directions of the impact of employees' job related attitudes on business-unit performance and vice versa within a four-wave dataset over a time span of four years. Data included two aspects of employees' job attitudes, that is overall job satisfaction and organizational commitment (Mowday, Steers, & Porter, 1979). The two performance indicators were business-unit financial performance and customer satisfaction.

In line with expectancy-based theories of motivation (e.g., Naylor, Pritchard, & Ilgen, 1980; Vroom, 1964) and adaptation-level theory (Helson, 1964) the results showed that employee attitudes had a more persistent influence on performance at the business unit level than vice-versa. In particular, we found that on a one-year basis, a reciprocal relationship between job attitudes and business-unit performance may exist. More importantly, the picture changed when we looked at the two-year lags because we found reasonably strong correlations between previous employee attitudes, consecutive financial performance and customer satisfaction, but not in the reversed direction. This pattern was consistent and could be repeatedly shown for various time lags for the influence of job satisfaction and organizational commitment on business performance, and for commitment on customer satisfaction.

Overall, the findings of the third study suggest that employee attitudes may come first and that practitioners who aim to increase performance by increasing employee attitudes might be

well advised to do so. Thereby our study was the first study conducted at the business-unit level including a four-wave sample and data from various data sources as diverse as employees' job attitudes, business-unit financial performance, and customer perceptions. It is the first empirical evidence to show that the influence of employee job attitudes on business-unit performance was more persistent than vice versa.

Overall, the findings of this thesis cover a broad range of topics directly related to human capital analytics as outlined in the introduction section. It helps to clarify the success factors of human capital analytics, compares methods of utility analysis in terms of managerial acceptance, and investigates basic assumptions inherent to the suggested alternative form of utility analysis. More specifically, we showed that the variables identified in the first study successfully discriminated between a more and a less accepted method of utility analysis, and gave an indication of what might be essential to gain managerial acceptance. Furthermore, we showed that a basic precondition for further developments in human capital analytics may be given, as the results from study three imply that improving employee attitudes actually does influence work related behavior, and finally leads to increased performance. This means that one of the basic preconditions of causal-chain analysis might be fulfilled. As the potential of such cost-benefit comparisons of attitude-behavior relationships has been described as enormous (Boudreau & Ramstad, 2007; Cascio & Boudreau, 2008) under the precondition that the causal flow goes from attitudes to performance, this is encouraging news both for academics and human capital management practitioners.

Strengths and Limitations

In what follows, I acknowledge particular strengths and weaknesses of the presented research. Today, the topic of human capital covers many different facets. For example, the last

SIOP conference (2009) in New Orleans set a strong focus on the human capital analytics topic, ranging from workshops on human capital risk management and symposiums on linkage research, to best practice seminars on what potentially valuable human resource metrics in practice might be. These events were accompanied by many presentations from representatives from well-known organizations such as Google, the FBI, and Starbucks. What became clear throughout the conference was that the topic was relatively unstructured: While some aspects of human capital analytics have a long tradition (e.g., linkage research, utility analysis), other important research questions have been left almost untouched (e.g., success factors of human resource information). One strength of this thesis is to discover such untapped domains and research questions, and to connect some of the most important aspects of this topic.

Furthermore, I systematically designed the three studies so that each study builds upon the previous one. The first study sought to answer the rather general question of potential success factors of human resource information in practice. The second study compared two forms of utility analysis methods along these variables and thereby both showed the practical usefulness of the variables discovered in study one, and simultaneously provided insights into a potentially powerful alternative to single attribute utility analysis, which is causal-chain analysis. As causal-chain analysis is based on the assumption that employee attitudes actually do influence organizational performance variables such as customer satisfaction and financial performance, the third study delivered some further encouraging evidence in favor of causal-chain analysis.

Throughout the thesis, we were concerned with high standards of methodological procedures. Study one used structural equation modeling to test the fit of the proposed human resource information success model with the collected data set. Study two set a strong focus on equal reading level statistics to prevent potential negative influence of reading ease on the results of the study. Additionally we applied the SPSS macro provided by Preacher and Hayes (2008) to

conduct the multiple mediation analysis, compared to testing separate simple mediation models. Study three introduced confidence intervals to get deeper insights into the results of a cross-lagged panel analysis by applying the SAS macro for nonoverlapping correlations described by Zou (2007), offering a variety of advantages over simple cross-lagged panel analysis and common confidence intervals, described in detail in the method section of Chapter 3.

A further strength of this study is its rigorous data collection methods. Study 1 and 2 both focused on a target population that usually is known as under heavy time pressure und therefore less available for research purposes, that is the management population of banks. This allows us to extend previous research that rather focused on HR practitioners (e.g., Haines & Petit, 1997; Macan & Highhouse, 1994).

Specifically in study 3, I had access to an exceptional database. In I/O research, a four-wave data set including three completely independent sources of highly reliable data is scarce and offers some great opportunities. Furthermore this data represented field data and offers a high level of generalizability to real world settings (c.f. Bortz & Döring, 2002). We strived to get the maximum out of the available data set by using the longitudinal nature of the data-set to focus on the issue of potential causal ordering, a research question that necessarily needs a longitudinal structure, ideally with a multitude of measurement-points. Beside the exceptional data-set, the third study took the endeavor to outline a theory that precisely predicted timely differences in the impact of employee attitudes on performance and vice versa. This is exceptional, as research often has done little more than say that one event will be followed by another (Mitchell & James, 2001). Therefore, little was known about the process of how long it takes for job attitudes to influence performance or vice versa (Riketta, 2008), and distinct hypothesis about which lasts longer were difficult to formulate in the past. Here our study shed new light on potential causal ordering.

On the other hand, the presented research has some limitations. Study one and two both used measures that were gathered from single questionnaires. This introduced the possible problem of common method bias, so that the results may be a result of the measurement process. However, in both cases we used Harman's one-factor test to address common method variance by including all items from all of the constructs in the study into a confirmatory factor analysis to determine whether the majority of the variance can be accounted for by one general factor (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). In both cases, this resulted in a very low model fit, indicating that common method variance may not be a problem. This went along with arguments that concerns about common method variance are likely to be overstated (Spector, 2006).

Specifically in study 3, our sample size with an average number of 34 business-units per year was relatively small. However, as this body of research asks for very specific criteria of the data set, small sample sizes are a common phenomenon (e.g., Koys, 2001, $n = 28$; Schneider & Bowen, 1985, $n = 28$; Schneider, Parkington, & Buxton, 1980, $n = 23$). Other weaknesses of the studies have been discussed in the respective chapter and are not addressed again here.

Implications for Research and Practice

The research of this thesis bears some important implications for research and practice. Some implications have already been described within the previous chapters. Here I will expand on the most important overarching topics.

In terms of future research, the human resource information success model offers a basis to evaluate a broad range of HR measurement alternatives. Single attribute utility analysis and causal-chain analysis are only two out of many different alternatives. Boudreau and Ramstad (2003) listed ten different approaches as possible HR alternatives, not including recent

developments such as the LAMP model (Cascio & Boudreau, 2008) or the HC Bridge model (Boudreau & Ramstad, 2003, 2005). As each method has its unique advantages and disadvantages, future research should evaluate both the appropriateness of the different methods in various settings, and evaluate the reactions of the target audience. Here, our theoretical model can provide guidance and provide the necessary theoretical framework to do so.

While we were able to show the superiority of causal-chain analysis over single attribute utility analysis, some further research is required to shed more light onto basic assumptions underlying the causal-chain analysis method of utility analysis, as outlined in study two. There are various open questions, for example which is the optimal measurement interval after a specific HRM intervention. Here we would expect that the optimal measurement interval differs, depending on the HR initiative implemented. Our suggestions of a combination of theories to specify timing issues in study three might be a promising starting point for further investigation in different settings. Especially the inclusion of the endowment/contrast model (Cheng, 2004; Tversky & Griffin, 1991) adds a lot of flexibility to our argumentation.

For practitioners, this thesis offers a variety of useful insights. First, the questionnaire used in this study has proven to be a reliable tool in the assessment of HRI attributes. The instrument might become a useful diagnostic tool for internal measurement of existing sources of HRI, and to detect problems within a company's available HRI. Whether a personnel selection procedure, a performance management system, or a method of utility analysis is under investigation, our survey can be used to assess it. It can also be used for external benchmarking. We would like to encourage practitioners to use our questionnaire, and to share their results. Over the years, and by spreading across different industries, this could provide a benchmark for companies to assess their individual HRI success index.

Over 30 years ago, some authors already suggested offering percentage improvement in productivity, based on improvements in job satisfaction as a potentially valuable means of expressing utility (Mirvis & Lawler, 1977). This represents the basic idea of causal-chain analysis and is supposed to be close to managers' cognitive processes. However, at that time, this approach offered many potential problems such as the role of stability of performance and attitudinal variables, the level of aggregation, the ideal timing of measurement, and issues of causal ordering (cf., Cascio & Boudreau, 2008). For many of these issues, today's research has progressed. In particular, study 3 of this thesis has addressed questions like the level of aggregation, timing issues and has gained insight into the potential causal ordering of these variables. Therefore, we suggest that practitioners increasingly focus on causal-chain analysis. The potential of such cost-benefit comparisons of attitude-behavior relationships in practice could be enormous (Boudreau & Ramstad, 2007; Cascio & Boudreau, 2008), but only makes sense if the causal flow goes from attitudes to performance. Our results indicate that the potential causal ordering might indeed be from job attitudes to performance, thus confirming the basic assumption of these initiatives.

Finally, study three sheds new light into the question of potential causal ordering of job related attitudes and performance and the results should be encouraging for practitioners who invest large sums into employee attitudes surveys, respectively into measures to improve the latter. However, human resource practitioners need to be aware that several studies have shown that there are natural limits to the amount to which employee attitudes can be improved (Bowling, Beehr, & Lepisto, 2006; Frederick & Loewenstein, 1999; Haidt, 2006; Tziner, Waismal-Manor, Vardi, & Brodman, 2008). Wright and Gardner (2005) noted that in much of the research on strategic human resources management (Huselid, 1995) the implicit presumption is that human resources practices and high-performance work practices have a direct effect on

employee attitudes that, in turn, yields improved individual and organizational performance. Yet, empirical evidence to support this implicit assumption is scarce (Wright et al., 2005). Here, research is challenged to apply designs similar to the ones applied in study 3 to strengthen the abovementioned implicit assumptions.

However, an alternative to measures intended to increase employee attitudes is the idea of applying personality questionnaires in personnel selection procedures. As Tziner et al. (2008) showed, work related attitudes are strongly related to personality. Furthermore, meta-analytical findings have shown that personality predicts performance (Barrick, Mount, & Judge, 2001; Ones, Dilchert, Viswesvaran, & Judge, 2007). Therefore, practitioners seeking to increase both employee attitudes and performance are well advised to use one of the several measures designed to assess personality.

Further Outcomes of this Study

This thesis would not have been possible without the close relation to and the practical experience I have been able to gather in the company I work for, which at this state shall be left unnamed. Throughout the last three years, I had the opportunity to work closely with many experienced managers and senior HR specialists, with whom I discussed the topics encompassed in this thesis from a practitioner's perspective. One of the outcomes of this practical assignment was the development of a human capital management dashboard, that is primarily built upon the considerations and the knowledge gained from the three studies described before. Its most important element is what we have been describing as causal-chain analysis and it has been built and implemented in that organization for the past two years (for a detailed description and screenshots see Wucknitz, 2009).

After two years of practical experience with the realization of a causal-chain analysis based dashboard, the post-implementation phase came up with some unexpected reactions. On the promising side, the logic and the appeal of a stringent and comprehensible analytical procedure as outlined by the causal-chain analysis approach of utility analysis created an unexpectedly large amount of management attention, even up to the most senior executive levels and far beyond the human capital management division of this organization. Besides the empirical evidence we gathered as outlined in chapter two, the key strength of causal-chain analysis seemed to unfold its strength not just in this scenario-based study, but also in practice. Furthermore, there had been a variety of practical examples of where this analytical procedure was influencing every-day managerial decisions such as the strategic focus of recruiting, the planning of training initiatives, and the realignment of compensation and goal-setting processes within that company.

On the pessimistic side, beside the challenges we have briefly mentioned in the discussion of study two during the construction phase of a causal-chain analysis based approach, we experienced some reluctance to adopt this new practice within the HR community of this organization. This is surprising, because one of the goals of human capital analytics is to increase the strategic advice-giving competency of the HR personnel, which is the reason we would have expected this part of the organization to react in a very positive manner. We can only speculate about the reasons for such behavior at this time. What became clear during the roll-out of the human capital management dashboard was that the transparency and tangibility of selected HR processes increased dramatically. This is not necessarily a desirable outcome to all parties involved, as it puts addition pressure and accountability on both the HR practitioners and the managers involved. In addition, the logic and rigor of such a fact-based analytical approach is contrary to the “gut-feeling” that sometimes is predominant in the HR world (Bassi & McMurrer,

2009; PWC, 2006): it requires a new way of thinking when it comes to human capital related decisions, particularly from HR advisers and HR business partners within an organization. Here, systematic training and introduction of HR personnel into the logic and the analytical procedures is required to turn the HR department as a whole into ambassadors of such new practices. On the side of the front-line management, we experienced both great interest in these new practices on one hand, but also some reluctance when it came to decision-making and implementation of insights out of such analysis on the other hand. Probably this is because what has been difficult to account for in the past suddenly requires the same attention as hard business figures such as financial indicators of business success. Therefore, we suggest that front-line managers should be closely involved in the construction phase, as this can help to establish this procedure as a decision-aid, rather then an additional controlling instrument. This is important, as many variables of human resource information can easily be manipulated (e.g., the results of an employee survey).

For these reasons, even though this thesis has shed some light on some important aspects of human capital analytics, future research should be continuously considered with the implementation of such causal-chain analysis in real-life scenarios and to systematically evaluate the reactions of both HR professionals and front-line managers. Furthermore it has not yet been determined whether the change in managerial decisions based upon insights gained out of a causal-chain analysis actually lead to an improvement in one of the intended bottom-line variables. This would be the final and probably most important part of demonstrating the value of any given human capital analytic procedure. However, such a research endeavor is challenging because longitudinal data is required, because there are no estimates available of what the potential impact might be, making it difficult to estimate the size of a required sample size, and because the number of potentially mediating variables might be large.

Finally, for the coming years, we expect the interest in the topic of human capital analytics to grow further. Despite the declining interest in some of the methods presented by I/O psychologists (Cascio & Aguinis, 2008), there are indicators that point to such an increase: In a recent survey of HR professionals from numerous industries, geographies and sizes that asked for their top ten priorities for 2008, selecting and monitoring high-impact HR performance indicators was ranked as a top priority among over 37% of respondents and ranked third out of ten (CLC, 2008). Consulting firms offer more and more advice and products designed to measure HR activity to provide useful information to decision makers (McKinsey: Harmon, Hensel, & Lukes, 2006; IBM: Lesser & DeMarco, 2006, and IBM, 2007; PWC, 2006). Human resource metrics databases and benchmarking tools have arisen to facilitate strategic decision making for practitioners (e.g., Saratoga, 2007). A recent study of the Corporate Leadership Council showed, that "An HR business partner's ability to use and create metrics can impact the strategic effectiveness by up to 21% and data analysis can impact this by up to 9%" (CLC, 2008), and the 2009 SIOP conference covered the human capital analytics topic with a large number of seminars, workshops, and symposiums.

With this thesis I hope to add to the growing knowledge in the field of human capital analytics on how to provide true expertise on how HR departments can provide strategic insights the business requires, to improve human capital related decisions, and to establish HR departments as true strategic partners that get acquitted of the constant pressure to demonstrate the value of what they do for the rest of the organization.

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Erklärung

Hiermit erkläre ich, dass ich die vorgelegte Arbeit selbst und ohne unzulässig Hilfe Dritter verfasst habe. Das bedeutet, dass ich hauptverantwortlich für die Planung, Durchführung und Auswertung der Studien war sowie die einzelnen Artikel, die in dieser Dissertation enthalten sind, federführend verfasst habe. Die als Koautoren ausgezeichneten Personen haben mich hierbei jeweils sprachlich, inhaltlich und/oder methodisch unterstützt und waren in begrenztem Umfang an der Konzeption und Durchführung der Studie oder an der inhaltlichen Gestaltung des Artikels beteiligt. Die Reihenfolge der Autorenschaft spiegelt den jeweiligen Grad der Unterstützung wieder.

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